DETERMINING TRANSIT IMPACT ON SEOUL OFFICE RENT AND LAND VALUE: AN APPLICATION OF SPATIAL ECONOMETRICS

A Dissertation

by

JIN KIM

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

December 2004

Major Subject: Urban and Regional Science

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Donald A. Sweeney (Co-Chair of Committee)	Ming Zhang (Co-Chair of Committee)
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ABSTRACT

Determining Transit Impact on Seoul Office Rent and Land Value: An Application of Spatial Econometrics. (December 2004)

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M.S., University of Seoul

Co-Chairs of Advisory Committee: Dr. Donald A. Sweeney

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This study posits that there may be a systematic bias in measuring the transit's endogenous impact on land values in a built up area due to discrimination by location in the city. Studies of transit value-added effect report mixed results about the capitalization of station proximity. The question is not whether a transit station influences nearby land values, but how and where location determines the impacts.

Examining 731 office rentals and land values in Seoul, this study finds that value premium over better accessibility to a station decays with increasing distance from the central business district (CBD) and significantly depends on the development density of the station area. Overall, station benefits seem to exist in Seoul, but they look more notable in centers with higher centrality. This makes a hierarchy of regression coefficients for station proximity by location, i.e. the beta in the CBD is the highest and those in the subcenters are next, while that in other areas is the lowest. Study findings imply that the potential of more compact and denser developments within station areas

seems higher in a dense inner city, providing evidence for the concept of ‘compact city.’

Questions concerning model specification in the hedonic approach are raised: in research sampled heavily from the suburbs, the coefficient may be underestimated where this benefit actually exists. Also, due to the incongruence of station area with station value-added area, using a dummy variable seems intrinsically risky.

This study shows that estimation with spatial models outperforms OLS estimation in the presence of spatial autocorrelation. Also, there is a strong spatial autocorrelation even in the SAR residuals where the omission of key variables still influences the estimation. Overall, spatial lag and error term variables greatly improve the fitness of regression equations; however, the latter seemed more useful than the former in this study. One thing to note is that the latter seems more sensitive to the choice of weight matrix than the lag variable. There may exist a unique weight scheme proper for the data structure which cannot be known in advance.

DEDICATION

To my wife, Moon, Jung Eun, who trusts the Lord and loves me with actions and in truth. I learned from her that love is patient and kind, does not envy or boast and is not proud. Thanks for her endless pray and encouragement for my academic achievement.

To my parents and younger sister, Hajin Kim, to whom I owe what I am.

To Jesus, with all the glory and praise.

ACKNOWLEDGEMENTS

I would like to express my sincere appreciation to my advisory committee members, Prof. Ming Zhang, Prof. Donald A. Sweeney, Prof. Christopher D. Ellis and Prof. Charles W. Graham, for their precious advice and eager to help during the dissertation works.

I give my special thanks to the SAMS Inc. Ltd. for their allowing me to use the valuable office data. I also appreciate lots of friends who helped and assisted me to finish my work. Specifically, Chun-man Cho, one of my best seniors in the department prayed the Lord for my graduation and marriage. Without Jung-mo Jang's help, I would not have crossed the bitterly troubled water. He did with all his heart what he could do. Even a brother would not help his disabled brother as he did for me. I thank Young-chol Park for his warm and kind advice whenever I need him. Finally, I give my best appreciation to faithful pastors, Young-sik Ahn, Chong Kim and Soon-ki Jung, who prayed and gave me unforgettable guidance when I lost my way.

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CHAPTER I

INTRODUCTION

Background

Despite intensive criticism, the concept of 'compact city' gains attention. As a sustainable model of developed cities, compact city is intended to induce higher density and mixed use development in the inner city with the support of efficient public transpo-rtation, e.g. transit systems, and by facilitating environment-friendly access modes such as walking and cycling. The claimed benefits sound dazzling: conservation of open space and natural environment, reduced auto travel and fuel emission, better access to services and development of more efficient infrastructure (Burton, 2000, pp. 1969-70).

Though based on a theoretical background different from compact city, a situation like that is found in transit-oriented development (TOD). It has a variety of definitions but in general is regarded as compact and mixed use development close to transit stations, which is conducive to transit ridership and eliminating auto trips. It is also legitimated to preserve open space and promote 'livable communities' and 'smart growth' (TRB, 2002, pp. 2-7).

The common implication of the two theories is to develop the urban structure to rely on public transit and to induce shifts in land use leading to more compact and denser activities near stations. Question is if a transit investment has enough potential to

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encourage intensive development in a geographical area close to and influenced by a transit station, the so-called 'transit station area' or just 'station area.' If transit stations increase economic benefits in station areas, higher-density developments can be expected in those areas, or vice versa (Huang, 1994).

In the literature, the market proxies frequently used to measure the benefits of station proximity are land value or commercial rent premiums on the grounds of the location theory in which the savings in travel costs are capitalized into higher land values or rents, i.e. station 'value-added' impact. If a transit investment is viable, higher value premiums are correlated with better accessibility to stations: a market-based green light for future land use changes.

This impact on land values can be cautiously classified as an 'endogenous impact' in an already built up area and 'exogenous impact' in a non-urban area. Research in the former is related to a cross-sectional analysis of the city, usually using a hedonic price model which regresses proximity to stations on property price or comparing the real estate performance, e.g. rental levels, vacancy rates and absorption rates, of properties within station areas with those of comparables farther from stations (Cervero, 1997). Studies on the latter trace changes in land values before and after a transit investment, in which case accuracy depends on selecting truly ex-ante control cases (Cervero et al., 1993).

With a heavy focus on single-family housing, most empirical studies on endogenous transit impact have revealed significant price premiums for accessibility to stations, generally in the six to seven percent range (Vessali, 1996). Nonetheless, zero or weak impact by station proximity was also reported (Gatzlaff et al., 1993). These mixed results look more striking in the studies on commercial property. At one extreme, substantial capitalization effects on retail and office rent are found (Cervero et al., 2002), and at the other extremes transit impact on values looks insignificant (Bollinger et al., 1998). Theoretically, since commercial land values are more sensitive to a change in travel cost than residential values in the bid rent model, or the price elasticity to accessibility to the station for commercial use is higher than that for residential use (Damn, 1980), the mixed results in commercial property is too confusing to interpret.

A possible explanation for the mixed reports in residence is the negative neighborhood effect for properties close to station, e.g. dust or noise (TRB, 2002, p. 37). Also, the transit quality or service a station belongs to can make these differences (Landis et al., 1995). In commercial properties, a possible reason is the relationship between the economic benefits of station proximity and land use policies encouraging intensive developments within station areas (Nelson, 1999). These explanations still leave a gap in knowledge regarding the role of location in the city in the mixed results.

There is a well-known precept in the real estate field: location, location, location. Difference in location not only makes the amenical features of each property different from those of others, the so-called ‘heterogeneity,’ but also affects the price for an equal amenity from one neighborhood to another, i.e. the existence of ‘submarkets.’ These two spatial phenomena occur simultaneously in all categories of property amenities. One thing to note is that accessibility to transit stations is also one of accessibility amenities, which may be determined by location in the city.

Problem Statement

This study asks if there is any systematic bias in examining the transit's impact on land values when the capitalization of station proximity is also discriminated by location in the city. Research does not ask whether a transit station influences nearby land values or not, instead, it asks how and where the impacts are determined by location.

In the land rent model, all the travel costs are non-linearly or more rapidly capitalized by a shorter distance to the central business district (CBD) because space users decrease their demand areas or consumption in response to increasing land values: the so-called 'substitution.' Considering that accessibility to a station is a type of travel cost, then it should also be capitalized more rapidly in station areas close to the CBD than in comparables far away. Also, the model implies that travel cost is more steeply capitalized in a denser city. Assuming that a station area is an independent unit, e.g. a city, then the capitalization of station proximity becomes steeper in a dense station area than in a less developed one.

Examining 731 office rentals and land values in Seoul, Korea, this study tests to see if accessibility to stations is also capitalized by a non-linear pattern which results in the economic benefits of station decay correlated to distance from the CBD and dependent upon development densities of station areas. The case was selected on the grounds of Seoul's high development density, well distributed subway system suitable for a cross-sectional analysis and a meaningful transit share of total passenger trips in the city. More details are explored in Chapter V. An affirmative study result confirms and provides the theoretical background to the conclusion by Nelson (1999). Also, this exploration attempts to explain the conflicting results regarding transit impact on land values and to shed light on a possible research risk with the hedonic model specification. Possibly, good news for a couple of outstanding urban paradigms, i.e. ‘compact city’ and ‘TOD.’

Two related methodological questions are raised regarding the discriminant transit impact on land values by location and density: one is the submarket effect and the other is the spatial autocorrelation in the regression residuals. A submarket can be defined as a geographic area where the market price per unit of an attribute is internally constant or homogeneous but differs substantially from others (Goodman et al., 1998). Since each submarket is influenced by unequal accessibility and neighborhood amenities, the study expects to show the different hedonic price from those of other submarkets for the same distance to a transit station: the regression coefficients for station proximity are discriminated by submarket in the city.

Discriminately and unidentically distributed location attributes cause a property value to be dependent upon nearby property values and the regression errors to be autocorrelated by location in the city, the so-called ‘spatial autocorrelation.’ If any form of autocorrelation exists in the ordinary least square (OLS) residuals, it makes the OLS estimation inefficient and the conclusion based on it problematic. Most literature describing spatial autocorrelation with a heavy focus on housing prices reports that the inclusion of nearby property values or a spatially lagged dependent variable in the model (SAR; spatial autoregressive model) can reduce the spatial dependency of OLS errors.

This study questions whether an autocorrelation remains even in the SAR residuals when the OLS estimation is extended to include the spatial lag and nearby properties' errors, i.e. the spatial error term. Between the lag and error terms, it also asks which one is more sensitive to the choice of spatial weight matrix which absorbs the collective impact of nearby properties. Reducing the spatial autocorrelation is expected to help the estimation model capture a more accurate and efficient parameter estimator for transit impact on commercial rent and land value.

Research Purpose and Objectives

The purpose of the study is to test the discriminant transit impact on office rents and land values in Seoul, Korea, by location in the city and reduce the spatial autocorrelation in the estimation residuals. More detailed research objectives are:

- to correlate the capitalization of accessibility to transit stations with distance from centers, e.g. the CBD and subcenters,
- to measure the possible dependency of capitalization of station proximity on development densities of station areas,
- to investigate the existence of submarkets regarding value premiums over station proximity,
- to test if there exists an autocorrelation in the SAR errors as well as in OLS errors and reduce it with the general spatial autocorrelation model (SAC) which extends the traditional hedonic model to include the spatial lag and the error term,
- to examine which one is more sensitive to the choice of spatial weight matrix between the spatial lag and error terms.

Research Hypotheses

Based on study objectives, the research hypotheses can be described as follows;

- Hypothesis 1: The economic benefits of station proximity ($\beta_{Station}$) decay correlated to distance from the centers, e.g. the CBD and the nearest subcenter.

  $H_{10}:\ \beta_{Station*DistToCenter} = 0$

  $H_{1a}:\ \beta_{Station*DistToCenter} > 0$

  where $\beta_{Station*DistToCenter}$ *denotes the interaction between the rent and value premiums over station proximity and distance to centers.*

- Hypothesis 2: If the development density of a station area increases, the economic benefits of station proximity ($\beta_{Station}$) increase larger.

  $H_{20}:\ \beta_{Station*Dev'tDensity} = 0$

  $H_{2a}:\ \beta_{Station*Dev'tDensity} < 0$

  where $\beta_{Station*Dev'tDensity}$ *denotes the interaction between the rent and value premiums over station proximity and the development densities of station areas.*

- Hypothesis 3: If station benefits are correlated with distance from the CBD and development density, then they may increase in centers with high centrality, or vice versa.

  $H_{30}:\ \left|\beta_{StationInCBD}\right| = \left|\beta_{StationInSubcenters}\right| = \left|\beta_{StationInOtherAreas}\right|$

  $H_{3a}:\ \left|\beta_{StationInCBD}\right| > \left|\beta_{StationInSubcenters}\right| > \left|\beta_{StationInOtherAreas}\right|$

  where $\beta_{StationInCBD}$, $\beta_{StationInSubcenters}$ *and* $\beta_{StationInOtherAreas}$ *denote the rent and* *value premiums over station proximity in the CBD, the subcenters and the other areas, respectively.*

- Hypothesis 4: If there exists an autocorrelation in the OLS residuals, the estimation models with the spatial lag and/or error terms will outperform the OLS.

  $H_{40}: \ TS_{OLS} = TS_{SM}$

  $H_{4a}: \ TS_{OLS} > TS_{SM}$

  where TS_{OLS} *and* TS_{SM} *denote the test statistics for model performances, e.g. log-likelihood ratios(LRs), mean sum of square due to regression errors (MSE) and standard errors(SEs) of coefficient estimates, by the OLS method and by the spatial model, respectively.*

- Hypothesis 5: If there exists an autocorrelation in the SAR residuals, the estimate with the SAC which contains the error term as well as the lag term will outperform that with the SAR.

  $H_{50}: \ TS_{SAR} = TS_{SAC}$

  $H_{5a}: \ TS_{SAR} > TS_{SAC}$

  where TS_{SAR} *and* TS_{SAC} *denote the test statistics for model performances by the SAR and the SAC, respectively.*

Significance of the Study

The most significant contribution of this study is to confirm the possible existence of a systematic bias in measuring value premiums over station proximity by location in the city, which can be captured by correlating the premiums with distance to centers. Theoretically, it proposes a possible explanation for the mixed results of transit impact on land values. Station benefits are not all the same across a metropolis; instead, they rely upon the urban structure and the development densities of station areas. This capitalization tendency is congruent with the expectations of location theory but only concerns currently built up urban areas, i.e. the endogenous impact. More seriously, this tendency belongs not solely to transit system but to all transportation modes with traffic nodes, e.g. highway ramps. This study also points out that this tendency does not distinguish commercial rents from land values which respond only to location amenities while the former relate to structural features as well as location attributes.

The results suggest that the potential for changes in land use leading to more compact and denser developments in station areas seems higher in dense inner cities, possible evidence of ‘compact city.’ These results are also applicable to the concept of ‘value capture,’ one of the most important rationales for transit joint development. It suggests that a transit development with expropriated properties near stations can finance project costs with increased land values and real estate taxes. This study shows that this financing method may not be successful in a built up suburb which already has some accessibility to employment centers.

Methodologically, this study suggests that the hedonic model specification should be cautiously applied to capture value premium regarding location attributes. Specifically, it implies that it is more probable for a study heavily sampled from centers to find a significant and large premium over station proximity and that a study on a built up suburbs would not find the same station benefit as in the inner city. The inconsequential impact of transit station on land value may be found in the city where this benefit actually exists.

Organization of the Dissertation

The following chapter reviews the literature regarding transit impact, specifically impact on land values, and discusses possible reasons and a gap in the knowledge for its mixed results. Also, it delves into studies of spatial autocorrelation in property research and raises several related questions.

Theoretical backgrounds are introduced in Chapter III with regard to discriminant transit impact on land values by location in the city and development density based on the land rent model in which all the travel costs are non-linearly capitalized into land rents. This chapter models the determining impacts on value premiums to test the research hypotheses. It also discusses the functional forms of spatial autocorrelation methods used in the study, e.g. the SAR, the SEM (Spatial Error Model) and the SAC.

Chapter IV develops the research models and selects the research variables. Two estimation models are designed to test the research hypotheses: Model 1 correlates accessibility to transit station with distance from centers and development density, and Model 2 examines the existence of submarkets in regard to station proximity. Also, this chapter considers the test statistics detecting a spatial autocorrelation in the estimation residuals and derives three spatial weight matrices reflecting the collective impact of nearby properties into the estimation.

Chapter V explains the structure, acquisition and validity of the surveyed data. Also, it explains the rationale for selecting the site and the significance of choosing Seoul. Descriptive statistics delineate a broad picture of Seoul office markets by submarket.

Analysis results discussed in Chapter VI test the hypotheses and compare the performance of estimation methods, i.e. the OLS, the SAR, the SEM. The test statistics are referenced to show there remains a strong spatial autocorrelation in the OLS and SAR residuals. Also, this chapter compares the performance of three weight schemes utilized by each spatial model.

CHAPTER II
LITERATURE REVIEW

Literature in Transit Impact on Land Use and Land Value

Public transportation in the study concerns the fixed-rail transit system which is believed to reduce travel time significantly in a metropolis. Among several types of transit systems, e.g. heavy rail, commuter rail and light rail, a heavy rail system is expected to decrease travel costs greatest because its service is more frequent and faster and its service area is much larger than others (Cervero et al., 2002, pp 10-1).

Literature in transit impact can be classified into three types: land use, land value, and urban form. Studies on land use impact concern the savings in total travel costs and land use change of suburban areas while research in land value impact is interested in the capitalization of economic benefits resulting from better accessibility to stations, the so-called ‘value-added effect.’ Literature concerning urban form can trace its origin to the earliest studies of the Chicago School sociologists. Its focus is transit investment and its consequent urban form changes (Goldberg et al., 1984, pp 521-3).

According to location theory, lower travel cost reduces rent slope, which increases land rent in the suburbs and decreases that of the CBD when there is no constraint for further urban expansion. This research approach, primarily focusing on changes in travel costs to the CBD, intrinsically depends on such methodology as a before-and-after study over time. Earlier BART studies in San Francisco (Fajans et al., 1978 and Falcke, 1978 in Vessali, 1996) and Boyce et al. (1972, in Vessali, ibid) in

Philadelphia attempted to correlate this increase of land rent with the change of land use, reporting that mass transit promoted the growth of suburbs and created a decline in the central city. However, a more recent study on the BART system by Cervero et al. (1995) reported that the station areas in the inner city showed faster growth than non-station areas, whereas the result is opposite in the suburbs.

These conflicting results imply that a suburb with no access to the CBD would be developed as an urban area at the initial stage but a transit investment would not be a motivation for a currently built up suburban area to change its residential use into higher density use: that is, the transit's salient exogenous impact but weak endogenous impact in the suburbs. This interpretation is based on the conclusion by Spengler (1930) that the transit investment in New York caused a development boom in a suburb which had no transportation infrastructures but did not induce a shift in land uses in well developed areas. More detailed explanation is explored in the next chapter.

Research on land value has attempted to correlate the economic benefits of station location with cross-sectional data analysis, e.g. a quasi-experimental study using similar comparables from different locations, the hedonic model regressing the property price or rent to accessibility to station, or a hybrid of these two methods (Cervero, 1997). The research risk of a quasi-experimental approach is that it is difficult to discern various confounding variables from station proximity and to find the exactly same comparables only except transit accessibility (Cervero et al., 1993).

Some housing studies reviewing the economic benefits of station proximity report successful results. A study by McMillen et al. (2004) on Chicago's Midway Rapid

Transit Line concludes that the increase in single-family house prices within station areas before and after opening the new line in 1993 is greater than that in comparables farther from the new transit stations. Armstrong (1994) report that there is approximately a 6.7% market value premium on single family residences neighboring rail transit in Boston. In a study by Benjamin et al. (1996) residential rents decreased by 2.4 to 2.6% for each one-tenth mile increase in distance from a Metro station in Washington D.C. Single family homes in Voith's study (1993) in Philadelphia showed a 7.5 to 8.0% value premium for accessibility to transit. Also, Haider et al. (2000) showed the effect of light rail transit (LRT) on housing prices in the Greater Toronto Area. In contrast, little or no impact by accessibility to station was also reported. A study by Gatzlaff et al. (1993) on the Miami Metrorail reported no effect with repeat sales data and weak distance impact with the hedonic model.

Unlike the housing studies, however, there have been very few reports on the capitalization benefits of proximity of rail transit to office or retail properties; results have been mixed. A study by Damm et al. (1980) on the Washington D.C. Metrorail found a significant price elasticity of -0.69 within 2,500 foot from a station. Cervero et al. (2002), on retail and office properties in Santa Clara County, California, reported the premium was as much as 23% for a typical commercial parcel near an LRT stop and more than 120% for commercial land in a business district within a quarter mile of a commuter rail station. On the contrary, Cervero et al. (1993) in a study of Atlanta and Washington D.C. and Landis et al. (1995) in the San Francisco Bay Area reported small or no economic impacts on commercial properties. Bollinger et al. (1998) conclude that proximity to a highway interchange has a positive effect on office rents while being within walking distance of a MARTA train station reduces rents.

A possible reason for conflicting results in residence may be the negative neighborhood effect for properties close to station, e.g. dust or noise. However, Dueker et al. (1998) researching Portland housing values conclude that the positive effect dominates the negative effect very soon and makes the largest price difference ($2,300) between the station and areas 200 feet away. Another explanation can be inferred from Landis et al. (1995) who concluded that a heavy rail system is more likely to impact property values than a light rail system. What distinguishes stations with transit impact from stations without it may depend upon the quality or service they offer. A finding by Nelson (1999) is most relevant to the mixed results on commercial properties and the focus of this study. It shows that commercial property values in midtown Atlanta are influenced positively by both accessibility to stations and policies that encourage more intensive development around those stations.

Korean Literature in Transit Impact on Land Use and Land Value

Studies on Seoul offices verified significant office rent premiums for accessibility to transit stations (Yang et al., 2001; Son et al., 2002; Lee et al., 2002b). Some of them found that about 500 meters is a significant distance in setting a station area (Kim et al., 2002) and a turning point of modal alternative to autos (Kim et al., 2001). Also, using 170 land price data, Kwon et al. (2001) find that the impact is more significant on property prices within station areas than those out-of station areas. Seo et al. (2001) examined the market segmentation effects on land values in Pusan, the second largest city of Korea, and found that the value premiums for accessibility to transit station are significant and important though less than the premiums for accessibility to the CBD.

However, office studies on Seoul dealt with three submarkets and none of them used the dataset across the city, which limits those results applied to the whole city. Still, no research has tried to measure the different rents and value premiums for station proximity due to different location factors.

Spatial Autocorrelation in Property Researches

In the presence of spatial autocorrelation, the estimation and the prediction with spatial models which extend the hedonic model to include the lag variable and/or the error term are more accurate and more robust than those with the OLS (Dubin, 2003). Since a major cause of positively autocorrelated error terms in research is the omission of key variables from the model (Dubin, 1998), earlier literature has asked if spatial dependency can be reduced by adding meaningful location or neighborhood variables. Dubin (1988) compared the OLS method and the ML method in the presence of spatial autocorrelation. Her result discovered that the OLS under the spatial dependency is biased but this bias can be alleviated by adding meaningful location or neighborhood variables. In her 1992 research, Dubin also eliminated all the locational attributes and kriged the house prices with the nearby house prices, which made a price contour map for Baltimore, Maryland. Basu et al. (1998), however, discovered that kringing the housing prices can make noises when the OLS assumptions hold.

Also, several studies have shown that the SAR model outperformed the OLS in the presence of spatial autocorrelation. Can (1992) reports that including the spatial lag variable can relieve the neighborhood quality effect and trace more efficiently the geographically disaggregated markets. A study by Carter et al. (2000) used the spatial lag variable to estimate the retail shops' rents in shopping malls. They found that adjusting the spatial autocorrelation significantly improved regression results and the fitness of the regression equation. Garrett et al. (2002), using the general spatial autocorrelation (SAC) model, reduces the spatial dependency of cross-border lottery shopping between a state and its neighbors. The error terms, however, do not prove statistically significant. Pace et al. (1998) show that the generalization of EGLS and OLS is the spatial autoregressive (SAR) model, which makes the SAR model applicable to both point and lattice pattern data. They also report that the SAR model is superior to the OLS method under the spatial autocorrelation (1997).

Chapter Summary

Literature in transit impact concerns the impact of transit investment on land use, land value, and urban form. Findings by studies on land use impact imply that a transit investment would develop a non-urban area as an urban suburb, specifically when it has no access mode to the CBD, but would not be a motivation for a built up suburb to change its residential use into higher density use: strong exogenous impact but weak endogenous impact in the suburbs.

Research on land value has correlated the economic benefits of station location with land value premiums. Some housing studies report successful results but others do little or no impact by station proximity. Unlike the housing studies, however, there has been very little literature in transit impact on commercial property values; results have been mixed. A possible explanation for the mixed reports in residence is the negative neighborhood effect for properties close to stations. Another explanation is the transit quality or service a station belongs to. In commercial properties, a possible reason may be the relationship between the economic benefits of station proximity and development densities within station areas.

Studies on Seoul offices verified significant office rent premiums for accessibility to transit stations. Some of them found that about 500 meters is a significant distance in setting a station area and a turning point of modal alternative to autos. However, there has been no literature dealing with the dataset for the whole city.

In the presence of spatial autocorrelation, the estimation and the prediction with the spatial models are more accurate and more robust than those with the OLS. Earlier studies have attempted to reduce the spatial autocorrelation by adding meaningful location or neighborhood variables or by including the spatial lag and/or error term variables. They report that adjusting the spatial autocorrelation significantly improved regression results and the fitness of the regression equation.

CHAPTER III

THEORETICAL FRAMEWORK

Non-linear Capitalization of Travel Cost Due to Substitution Effect

Public investments in transportation are expected to reduce the commuting costs, which in the long run decrease land rent all across the city.[1] Land rent can be defined as the price of rights to use a landowner's land per unit at a specific location in a city during a specific time period (O'Sullivan, 1996, p. 167). To construct a theoretical framework for the relationship between transportation cost and land rent, let us make several Ricardian assumptions in a mono-centric city: a fixed and even density in the city and a single employment center to which commuting costs t dollars annually per mile. Thus, travel cost of a household located at u miles from the CBD is equal to tu dollars annually. Also, households are identical: the number of workers per household and household income (Y) are the same for all households (DiPasquale et al., 1996, pp. 36-7).

Y can be spent only on non-housing (N), housing (H) and commuting (t). Housing consumption depends on land rent per unit ($R(u)$) at u miles from the CBD, i.e. the demand square foot (H) increases as $R(u)$ decreases, the so-called housing substitution. Land is occupied by households which offer the highest rent. Then, the

1 With several assumptions, land price is also linearly related to land price. Let us assume that the land value at time t (V_t) is a discounted cash flow of land rent (R_t) in perpetuity, at an expected rate of return (r), then V_t is defined as following:

$$V_t = \sum_{i=1}^{\infty} \frac{R_t}{(1+r)^i} = \frac{R_t}{r}$$

consumption of a household at u miles from the CBD can be written as follows:

(1) $$Y = PN(u) + R(u)H(u) + tu$$

while P is the price of non-housing consumption per unit. When a consumer's utility with the consumption of $N(u)$ and $H(u)$ is on the indifference curve, Formula (1) is in the equilibrium with the following requirement:

(2) $$P \times \frac{\partial N(u)}{\partial u} + R(u) \times \frac{\partial H(u)}{\partial u} = 0$$

Partially differentiating Formula (1) regarding u produces the rent gradient at location u, as follows:

(3) $$P \times \frac{\partial N(u)}{\partial u} + \frac{\partial R(u)}{\partial u} \times H(u) + R(u) \times \frac{\partial H(u)}{\partial u} + t = 0$$

When Formula (2) is subtracted from Formula (3), the arranged are as follows:

(4) $$\frac{\partial R(u)}{\partial u} \times H(u) = -t$$

(5) $$\frac{\partial R(u)}{\partial u} = -\frac{t}{H(u)}$$

At a given location (u), rent gradient ($\partial R(u)/\partial u$) is determined as travel cost divided by housing consumption ($H(u)$) of which substitution makes rent function non-linearly related to u. With a shorter distance to the CBD, $R(u)$ increases faster than linearly as u decreases. The easier the change in housing consumption, the steeper the rent gradient is expected. Let us define this non-linear capitalization of travel cost due to housing consumption as 'substitution effect.' The convexity of rent curve is also verified by differentiating Formula (5) regarding u, as follows:

$$(6) \qquad \frac{\partial}{\partial u}\left[\frac{\partial R(u)}{\partial u}\right] = \frac{\partial^2 R(u)}{\partial u^2} = \left[\frac{t}{\{H(u)\}^2}\right]\left[\frac{\partial H(u)}{\partial u}\right] > 0$$

Using Formula (5), a bid rent curve for housing service in a mono-centric city is illustrated in Figure 1. Other things being equal, the steeper the gradient, the higher the land rent and the shorter the city limit and vice versa. Formula (5) implies that lower travel cost (t) reduces rent slope ($\partial R / \partial u$), which increases relative land rent in a suburb and decreases the importance of the CBD.

Changing Formula (1), office bid rent function can be derived with similar assumptions: a fixed and even density in a city, a single employment center and identical firms. Under the zero profit condition, total revenue (Y) is allocated to capital (K), lab-

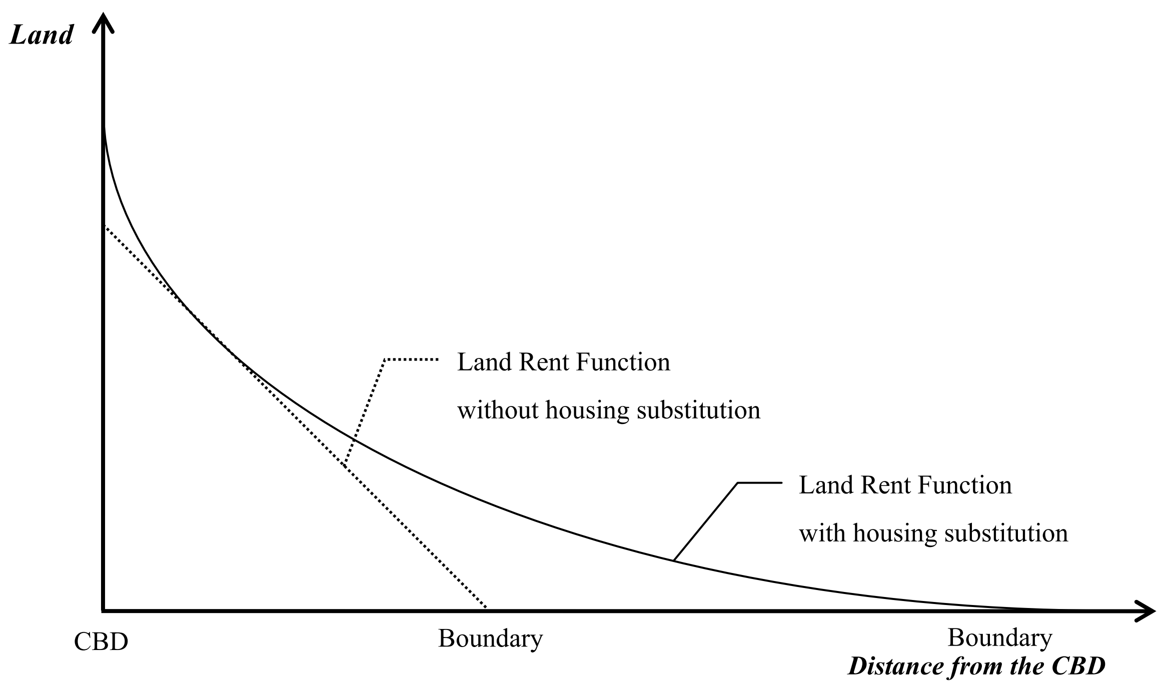

Figure 1. Housing Land Rent Function in a Mono-centric City

or (L), rent (R) and travel costs (t) for face-to-face contact with customers, relevant firms and business services. Office space consumption follows the demand schedule, i.e. the increasing demand square footage (O) for the decreasing R. The consumption of an office firm which is located at u miles from the CBD can be denoted as following:

$$Y = CK + W(u)L(u) + R(u)O(u) + tu \tag{7}$$

while C is the cost of capital per dollar and $W(u)$ is the wage per employee at a given location (u). With the same partial differentiation steps, an office firm's transportation cost and land rent can be arranged as follows:

$$L(u) \times \frac{\partial W(u)}{\partial u} + \frac{\partial R(u)}{\partial u} \times O(u) = -t \tag{8}$$

$$\frac{\partial R(u)}{\partial u} = -\frac{1}{O(u)}\left[t + \frac{\partial W(u)}{\partial u} \times L(u)\right] = -\frac{t}{O(u)} - \frac{\partial W(u)}{\partial u} \times \frac{L(u)}{O(u)} \tag{9}$$

Office rent gradient ($\partial R(u)/\partial u$) increases as commuting cost increases, or it decreases as office space consumption increases. Since the wage function ($\partial W(u)/\partial u$) is negative, the increase of $\partial W(u)/\partial u$ makes land rent lower and firms' locations more decentralized in the city. Also, the bigger the firm size ($L(u)$), the less attractive the location in the CBD. If we assume that $\partial W(u)/\partial u$ is zero, Formula (9) is equal to Formula (5). Office rent function is also non-linear: $R(u)$ increases more rapidly as $O(u)$ decreases with shorter distance to the CBD. Also, the bid rent curve for office firms in a mono-centric city is the same as that illustrated in Figure 1.

Formulas (5) and (9) suggest that lower travel cost (t) reduces rent gradient ($\partial R/\partial u$). Figure 2 shows two cases: one is spatially constrained and the other is not.

When there is no constraint for urban expansion, lower t reduces land rent from $R(u)_0$ to $R(u)_1$ and enlarges the city limit from B_0 to B_1. Such density-reducing result of transportation improvements increases land rents in the suburbs and decreases those in the CBD. The relative importance of the CBD diminishes, but the total sum of rents in the city may rise. Though a further expansion of city is limited, lower t from a new transportation investment decreases the aggregate level of land rent in the city. Thus, a transportation investment not only reduces travel cost but lowers rent payments, which increase real productivity in the city and make more income available to both households and firms for the purchase of other goods and services (Geltner et al., 2001, pp. 76-80).

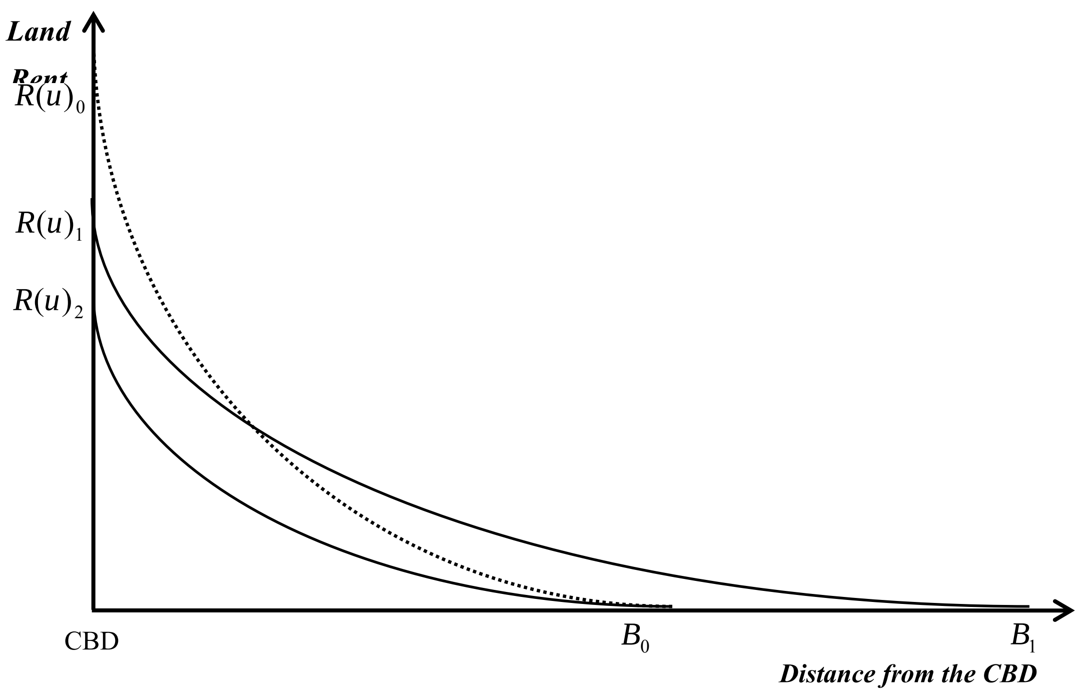

Figure 2. Impact of Reduction in Transportation Cost on Land Rent

Besides, since a lower cost of transit than that of autos causes some commuters to switch from autos to transit, the cost of autos will also decrease. Thus, public investment on transit is expected to lower transportation costs all across the city.

Travel cost of transit (t) can be divided into four cost elements: collection time (C), line-haul time (L), distribution time (D), and monetary cost for the trip (M) (O'Sullivan, 1996, pp. 590-1). Then, t can be denoted as follows:

(10) $$t = f(C, L, D, M)$$

There are a couple of general conclusions from empirical studies on transit ridership: first, the transit demand is more sensitive to the travel time ($C + T + D$) than the monetary cost (M). The other is that the VOT (value of time) spent in $C + D$ is two to three times larger than the VOT in T (O'Sullivan, 1996, pp. 589-92). Transit system is one of the cheapest modes only regarding the monetary cost which is sometimes equal in a city, e.g. Seoul, Korea. Also, the British experience that attempts by city authorities to convert auto commuters to transit by subsiding public transport fares have mainly proved unsuccessful implies the demand for transit is almost insensitive to the fare levels of mass transit (Button, 1993, pp. 46-7).

Discriminant Transit Impact on Land Rent by Location in the City

As seen in Formulas (5) and (9), travel cost is non-linearly capitalized in land rent mainly due to housing and office consumption substitution ($H(u)$ and $O(u)$, respectively). When this tendency is also applicable to land rent over station proximity, land rent slope over station proximity is discriminated by distance from the CBD.

To build a conceptual model, it is critical to determine distance (u) concept in the land rent model. It implicitly assumes a time distance equal for any location with the same access time to the CBD. In reality, however, it is more probably a physical distance. Another critical determination is whether the model adopts the concept of nodes, e.g. highway ramps and subway stations, because it decides travel pattern and cost.

Time Distance Concept. Let us assume u is time distance which is all equal for any location with the same access time to the CBD. Also, suppose that no monetary cost difference in the city, i.e. $\partial M / \partial u$ is zero, and a commuter's travel consists of distance to the nearest station (d_2) and line-haul distance between the station and the CBD (d_1), i.e. no distribution considered. No commuter is allowed to access the CBD directly without using stations. Then, total travel time (T) is constrained as the sum of line-haul time (T_1) and access time to station (T_2), as follows:

(11) $$u = T = T_1 + T_2 = \frac{d_1}{L} + \frac{d_2}{A}$$

while L is the line-haul speed between station and the CBD, and A denotes the access speed to the nearest station. Both are supposed to be greater than one. The relationship between travel cost (tu) and household consumption (Y) in Formula (1) is sustained, i.e. rent gradient regarding u ($\partial R / \partial u$) is the same as Formula (5). Then, the partial relationship of d_1 and d_2 regarding u can be defined, as follows:

(12) $$Y = PN(u) + R(u)H(u) + t\left(\frac{d_1}{L} + \frac{d_2}{A}\right) + M$$

(13) $$\frac{\partial u}{\partial d_1} = \frac{1}{L} \text{ and } \frac{\partial u}{\partial d_2} = \frac{1}{A}$$

Then, rent slope over accessibility to station ($\partial R / \partial d_2$) can be defined as follows:

(14) $$\frac{\partial R}{\partial d_2} = \frac{\partial R}{\partial u} \times \frac{\partial u}{\partial d_2} = -\frac{t}{H(u)} \times \frac{1}{A}$$

$$\frac{\partial R}{\partial d_1} = \frac{\partial R}{\partial u} \times \frac{\partial u}{\partial d_1} = -\frac{t}{H(u)} \times \frac{1}{L}$$

$$\lim_{u \to 0} \frac{\partial R}{\partial d_2} = -\infty \text{ and } \lim_{u \to \infty} \frac{\partial R}{\partial d_2} = 0$$

Since the access speed to station (A) is assumed to be greater than one, Formula (14) implies that $\partial R / \partial d_2$ is less than $\partial R / \partial u$. The benefit of station proximity is more rapidly capitalized in the CBD than in the suburbs due to the substitution effect. The same interpretation is applicable to land rent over line-haul distance ($\partial R / \partial d_1$) unless housing substitution ($H(u)$) is nullified. Also, as A increases with a public investment, e.g. bicycle or various pooling system, the capitalization of this benefit decreases. Let us assume a commuter's 'perceived line-haul distance (d_1')' is influenced by access speed (A), as follows:

(15) $$d_1' = d_1 + \frac{\partial d_1}{\partial d_2} \times d_2 = d_1 + \frac{L}{A} \times d_2$$

Since it is not easy either to change d_1 and d_2 unless a commuter moves to another neighborhood or to decrease the line-haul speed (L) due to competition with other transportation modes, his perceived line-haul distance depends on the access speed to station (A). As A increases with a public investment, his perceived distance to the CBD can be lowered, which may increase transit ridership. Since it is not the issue of the study, no further exploration is ventured. However, there is evidence that the cost competitiveness of a transit system exists only if it can reduce collection and distribution time as well as line-haul time. Travelers, specifically regarding longer routes, tend not to perceive small line-haul time savings or cannot utilize such time savings (Tipping, 1968 in Button, 1993, p. 57).

Physical Distance Concept. When u is a physical distance, the model is influenced by travel pattern. Let us assume that travel pattern sustains an approximately orthogonal relationship between d_1 and d_2, as seen in Figure 3. This assumption is invalid for transportation modes with limited nodes and is eliminated later in this chapter.

Every commuter must pass by his nearest station which locates all across the subway line, and total travel time (T) is equally constrained by Formula (11). Let the coordinates of the CBD, a household and its nearest station be pointed out at the starting point (0,0), (x_1, Δy) and (x_1, 0), respectively. Then, d_1 and d_2 are equal to x_1 and Δy, respectively. Also, u can be defined as follows:

(16) $$u = \sqrt{d_1^2 + d_2^2}$$

The relationship between a household's consumption and travel distance is also modified as follows:

(17) $$Y = PN(u) + R(u)H(u) + t\sqrt{d_1^2 + d_2^2} + M$$

Partially differentiating Formula (16) produces the relationship between distance

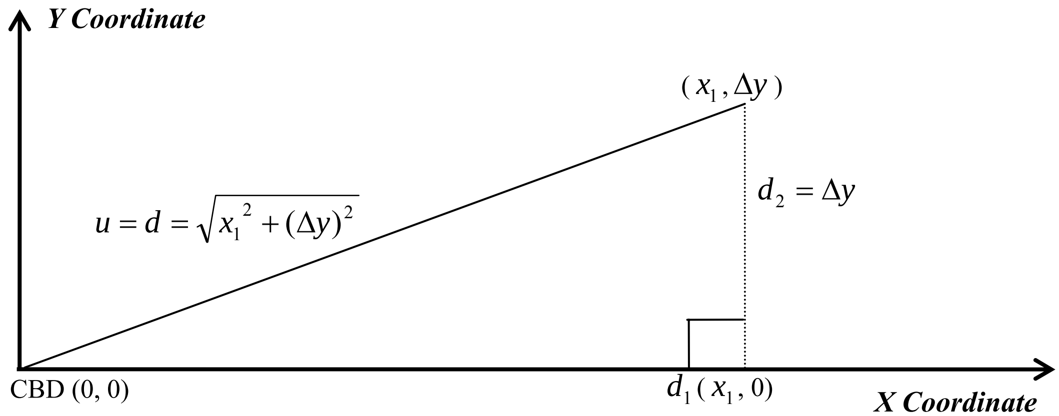

Figure 3. Limited Location of Household with Orthogonal Relationship

to the CBD and accessibility to station, i.e. $\partial u / \partial d_2$, and land rent slope over station proximity ($\partial R / \partial d_2$), as follows:

(18) $$\frac{\partial u}{\partial d_2} = \frac{d_2}{\sqrt{d_1^2 + d_2^2}} = \frac{d_2}{u}$$

(19) $$\frac{\partial R}{\partial d_2} = \frac{\partial R}{\partial u} \times \frac{\partial u}{\partial d_2} = -\frac{t}{H(u)} \times \frac{d_2}{u}$$

$$\frac{\partial R}{\partial d_1} = \frac{\partial R}{\partial u} \times \frac{\partial u}{\partial d_1} = -\frac{t}{H(u)} \times \frac{d_1}{u}$$

$$\lim_{u \to 0} \frac{\partial R}{\partial d_2} = -\infty \quad \text{and} \quad \lim_{u \to \infty} \frac{\partial R}{\partial d_2} = 0$$

Formula (19) implies that land rent should be more sensitive to the changes of station proximity in the CBD than in the suburbs. The same result is expected for rent slope over line-haul distance ($\partial R / \partial d_1$). When d_2 is constrained as $0 \le d_2 \le k \le u$, where k denotes the maximum accessible distance to station, $\partial R / \partial d_1$ is approximate to land rent gradient ($\partial R / \partial u$), specifically in the suburban areas. In contrast, the ratio of

$\partial R / \partial d_2$ to $\partial R / \partial u$ converges to zero with increasing distance from the CBD: that is, the net impact of station proximity on land rent becomes weaker.

The orthogonal assumption in Formula (16) sustains the independence between d_1 and d_2. Though, there still remains dependency between u and d_2 because further distance from a station (d_2) inevitably increases further distance from the CBD (u) with Formula (16). It threatens the most critical underlying assumption of the hedonic model, independency between explanatory variables. Rent premiums over station proximity ($\partial R / \partial d_2$) significantly depend on land rent on distance from the CBD ($\partial R / \partial u$). Also, this assumption is applicable only to the transportation modes like autos of which accessibility are not limited with several nodes, e.g. highway ramps or stations. When the constraint in Formula (16) is loosened to adopt the limited number of stations on the subway line, the location of a household is also free from that constraint.

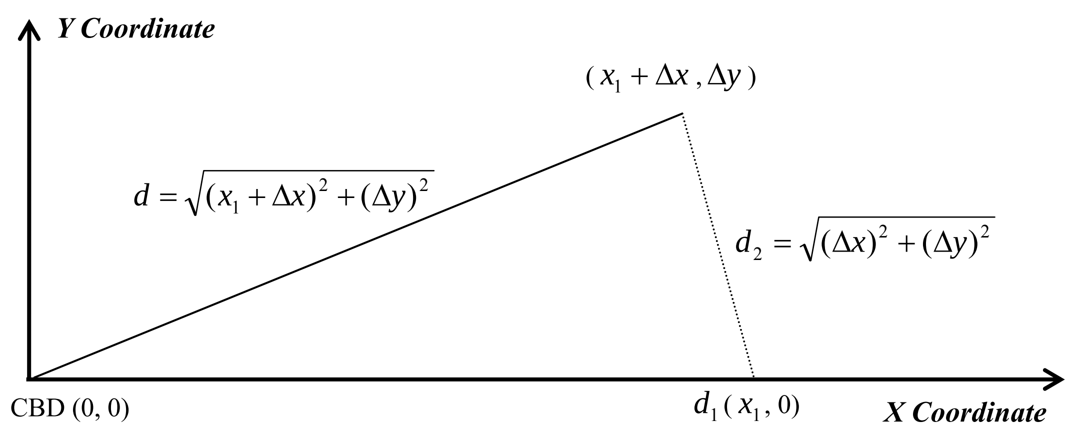

Figure 4. Unlimited Location of Household without Orthogonal Relationship

Suppose the locations of the CBD (0,0) and station ($x_1, 0$) are the same as previous. Assume a household at location ($x_1 + \Delta x$, Δy), then new d_2 and u can be defined as follows:[2]

(20) $$d_2 = \sqrt{(\Delta x)^2 + (\Delta y)^2}$$

$$u^2 = (x_1 + \Delta x)^2 + (\Delta y)^2 = x_1^2 + 2x_1\Delta x + (\Delta x)^2 + (\Delta y)^2 = d_1^2 + d_2^2 + 2d_1 d_2 \cos\theta$$

When Δx is equal to zero, Formula (20) is the same as Formula (16). Partially differentiating Formula (20) regarding d_2, a new land rent slope for station proximity ($\partial R / \partial d_2$) can be obtained as follows:

(21) $$\frac{\partial u}{\partial d_1} = \frac{1}{u}\left[d_1 + d_2 \cos\theta\right] \text{ and } \frac{\partial u}{\partial d_2} = \frac{1}{u}\left[d_2 + d_1 \cos\theta\right]$$

(22) $$\frac{\partial R}{\partial d_1} = -\frac{t}{H(u)} \times \frac{d_1 + d_2 \cos\theta}{u}$$

$$\frac{\partial R}{\partial d_2} = -\frac{t}{H(u)} \times \frac{d_2 + d_1 \cos\theta}{u}$$

$$\lim_{u \to 0} \frac{\partial R}{\partial d_2} = -\infty \text{ and } \lim_{u \to \infty} \frac{\partial R}{\partial d_2} = 0$$

Now, the solutions of Formula (22) also verify that $\partial R / \partial d_2$ is higher in the CBD than in the suburbs. As u goes to zero, $\partial R / \partial d_2$ converges to negative infinity, while it converges to zero with increasing distance from the CBD. Since the maximum

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2 This study used polar coordinate for $\partial \Delta x / \partial d_2$: let any random point ($x_1 + \Delta x$, Δy) within a station area be related to d_2 as follows:

$\Delta x = d_2 \cos\theta$ and $\Delta y = d_2 \sin\theta$

Since θ is indifferent to d_2, the partial relationship between Δx and d_2 is defined as follows:

$\partial \Delta x / \partial d_2 = \cos\theta$

value of d_2 is constrained as k, $\partial R/\partial d_1$ is approximate to land rent gradient ($\partial R/\partial u$) and the ratio of $\partial R/\partial d_2$ to $\partial R/\partial u$ converges to zero as d_1 approaches infinity.

Since, without the assumption of negative impact on residential environment, $\partial R/\partial d_2$ is believed to be negative, the potential interval of $\partial u/\partial d_2$ is between zero and one.

(23) $$0 \leq \frac{\partial u}{\partial d_2} = \frac{1}{u}\left[d_2 + d_1 \cos\theta\right] \leq 1$$

Also, since it is hard to build a house on a railroad, i.e. on the $x-$axis, the interval of $\cos\theta$ does not contain one ($-1 < \cos\theta < 1$). $\partial u/\partial d_2$ in Formula (21) is constrained as follows:

(24) $$0 \leq \frac{d_2 - d_1}{u} \leq \frac{\partial u}{\partial d_2} = \frac{1}{u}\left[d_2 + d_1 \cos\theta\right] \leq \frac{d_1 + d_2}{u} \leq 1$$

When $\cos\theta$ is equal to zero or the orthogonal relationship between d_1 and d_2 holds, Formula (22) is exactly the same as Formula (19). When $\cos\theta$ is greater than zero, $\partial R/\partial d_2$ is greater than the net benefits of station proximity ($\left[\partial R/\partial d_2\right]_{\Delta x=\cos\theta=0}$), or vice versa. Thus, a station area where $\cos\theta$ is positive or $x_1 + \Delta x$ is greater than x_1 has a steeper slope than station area where $\cos\theta$ is negative. The influence of $\partial R/\partial d_1$ is minimal when $\cos\theta$ is zero, while it is most dominant when $\cos\theta$ is minus one or plus one, i.e. on the railroad. Then, Formula (22) can be rewritten as follows:

(25) $$\frac{\partial R}{\partial d_2} = -\frac{t}{H(u)} \times \frac{d_2 + d_1 \cos\theta}{u} = \left[\frac{\partial R}{\partial d_2}\right]_{\Delta x=0} + \left[\frac{\partial R}{\partial d_1}\right]_{\Delta x=0} \times \cos\theta$$

When Δx is zero, $\partial R/\partial d_2$ is the net rent premium over station proximity, which does not make $\partial R/\partial d_1$ matter. The latter term ($[\partial R/\partial d_1]_{\Delta x=0} \times \cos\theta$) can be interpreted as the interaction between the location of household in station area ($\cos\theta$) and land rent slope at that station ($\partial R/\partial d_1$) or line-haul time impact on $\partial R/\partial d_2$. Thus, $\partial R/\partial d_2$ contains two types of transit impact: one is the net benefit of access to station and the other is its interaction with line-haul ($[\partial R/\partial d_1]_{\Delta x=0} \times \cos\theta$). The relative importance of this interaction in parenthesis relies on the ratio of d_1 to u, i.e. (d_1/u). Holding d_2 between 0 and k, its relative importance in $(d_2 + d_1\cos\theta)/u$ converges to zero as d_1/u goes to zero. On the contrary, as d_1 goes to u, e.g. in the suburbs, its relative importance increases until it almost approximates the net station impact ($[\partial R/\partial d_2]_{\Delta x=0}$) into zero. Other things being equal, as d_1/u increases or d_2/u decreases, this importance increases, or the vice versa. Therefore, commuters in the CBD pay higher land rent in the station area for access time to station ($[\partial u/\partial d_2]_{\Delta x=0}$) and those in the suburbs for line-haul time savings ($[\partial u/\partial d_1]_{\Delta x=0} \times \cos\theta$). This indicates why developments in the suburbs show less dependency on accessibility to subway stations or highway ramps. The explanation becomes clearer when u is transformed into a function with T_1 and T_2 as follows:

(26) $$u^2 = d_1^2 + d_2^2 + 2d_1d_2\cos\theta = L^2T_1^2 + A^2T_2^2 + 2ALT_1T_2\cos\theta$$

(27) $$\frac{\partial u}{\partial T_1} = \frac{1}{u}\left[L^2T_1 + ALT_2\cos\theta\right] \text{ and } \frac{\partial u}{\partial T_2} = \frac{1}{u}\left[A^2T_2 + ALT_1\cos\theta\right]$$

(28) $$\frac{\partial R}{\partial T_1} = -\frac{t}{H(u)} \times \frac{L^2T_1 + ALT_2\cos\theta}{u} \text{ and } \frac{\partial R}{\partial T_2} = -\frac{t}{H(u)} \times \frac{A^2T_2 + ALT_1\cos\theta}{u}$$

Obviously, as T_1 increases or the L increases, the line-haul benefits become more capitalized into $\partial R / \partial d_2$. However, it does not mean a rent premium with this interaction ($\left[\partial R / \partial d_1\right]_{\Delta x=0} \times \cos\theta$) is greater in the suburbs than in the CBD. As seen in Formula (23), the term $\partial u / \partial d_2$ is fixed between zero and one while the denominator ($H(u)$) increases geometrically. The capitalization of this interaction term rapidly becomes smaller in the suburbs. Also, when the sample is well distributed within station area, this interaction is expected to be a trade off with both plus and minus signs.

Another implication from Formula (23) is related to the research scheme to discern distance between properties along a subway line and properties whose distance is orthogonal to a line. Clearly, as d_1 increases, $|\cos\theta|$ becomes smaller to fulfill Formula (23): the economic benefits of proximity to transit stations ($\partial R / \partial d_2$) appear more clearly in the orthogonal location of household to a subway line. This is why $\partial R / \partial d_2$ of properties along the line is less than that of comparables orthogonal to the line which are the same distance from stations.

The economic benefits of station areas ($\partial R / \partial d_2$) may depend not only upon net station proximity ($\left[\partial u / \partial d_2\right]_{\Delta x=0}$) but also upon line-haul benefits ($\left[\partial R / \partial d_1\right]_{\Delta x=0} \times \cos\theta$). The latter almost replaces the former in the suburbs, but disappears rapidly and is not easily measured in a well distributed sample. Thus, is it necessary to derive the net benefits of station proximity from total station benefits ($\partial R / \partial d_2$)? The concept of transit impact contains both in a body. Problem lies where the line-haul benefits are not easy to be captured with usual model specification in the hedonic approach.

Here lies a research risk, specifically in the suburbs. When a sample concentrates on the suburbs, the beta of this variable may be underestimated, partly due to the substitution effect and partly due to the excessive absorption of insignificant station benefits except in properties orthogonally located to a transit line. The inconsequential impact of station proximity on land value may be found in the city where this economic benefit actually exists.

Does this risk belong only to a subway system? All the studies on transportation impact on land values should consider that the net impact is lower in the suburb. Specifically, a research regarding transportation modes with traffic nodes, e.g. highway ramps, needs to be cautious that the economic benefits of node proximity is less capitalized in the suburbs, partly due to the substitution effect and partly due to not absorbing the interactions between node proximity and line-haul time saving benefits.

Since $\partial R / \partial u$ and $\partial R / \partial d_2$ have different denominators which make the rent graph three-dimensional, i.e. R, d_2 and u axis's, not u but d_1 should be the X-axis in a 2-D graph where Δy is zero. $\partial R / d_1$ and $\partial R / \partial d_2$ sustains the relationship with $\partial R / \partial u$ as follows:[3]

(29) $$\frac{\partial R(u)}{\partial u} \times u = \frac{\partial R}{\partial d_1} \times d_1 + \frac{\partial R}{\partial d_2} \times d_2$$

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3 Formula (22) is also legitimated to fulfill the condition in Formula (29). The right side of equation in Formula (29) can be solved as follows:

$$\frac{\partial R}{\partial d_1} \times d_1 + \frac{\partial R}{\partial d_2} \times d_2 = -\frac{t}{H(u)} \times \frac{d_1(d_1 + d_2 \cos\theta)}{u} - \frac{t}{H(u)} \times \frac{d_2(d_2 + d_1 \cos\theta)}{u}$$

$$= -\frac{t}{H(u)} \times \frac{d_1^2 + d_2^2 + 2d_1 d_2 \cos\theta}{u} = -\frac{t}{H(u)} \times \frac{u^2}{u} = -\frac{t}{H(u)} \times u = \frac{\partial R(u)}{\partial u} \times u$$

$$\therefore \frac{\partial R(u)}{\partial u} \times u = \frac{\partial R}{\partial d_1} \times d_1 + \frac{\partial R(u)}{\partial d_2} \times d_2$$

Figure 6 integrates these two partial slopes of Figure 5 in a graph, which shows land rent curve responding not to u but to d_1. It gives a couple of implications for studies on transit impact on land value: one is station value-added area and the other is related to the validity of the hedonic model. Let us define 'station value-added area' as the area between the minimum land rents centering a station along the railroad (d_1), i.e. $\partial R / \partial d_1 = 0$. It is necessary to discern it from 'station area' because the latter primarily relates to the limit of physically accessible distance to station, i.e. k.

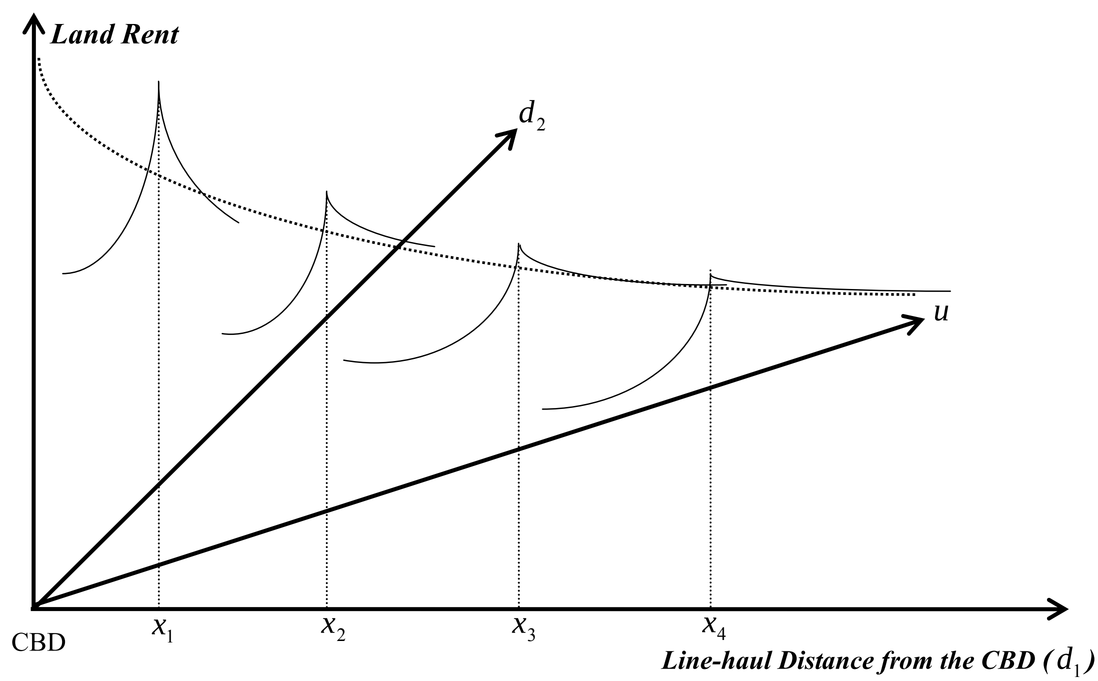

Figure 5. Land Rent Curves for Station Proximity and Distance from the CBD

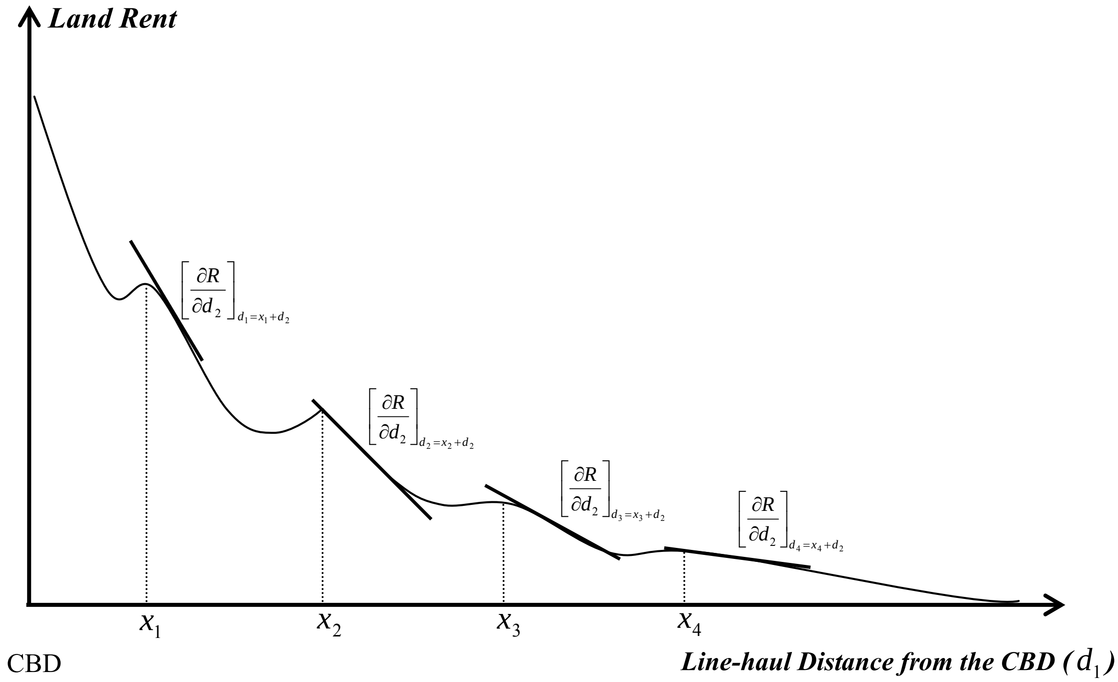

Figure 6. Partial Coefficient of Station Proximity on Land Rent along Railroad

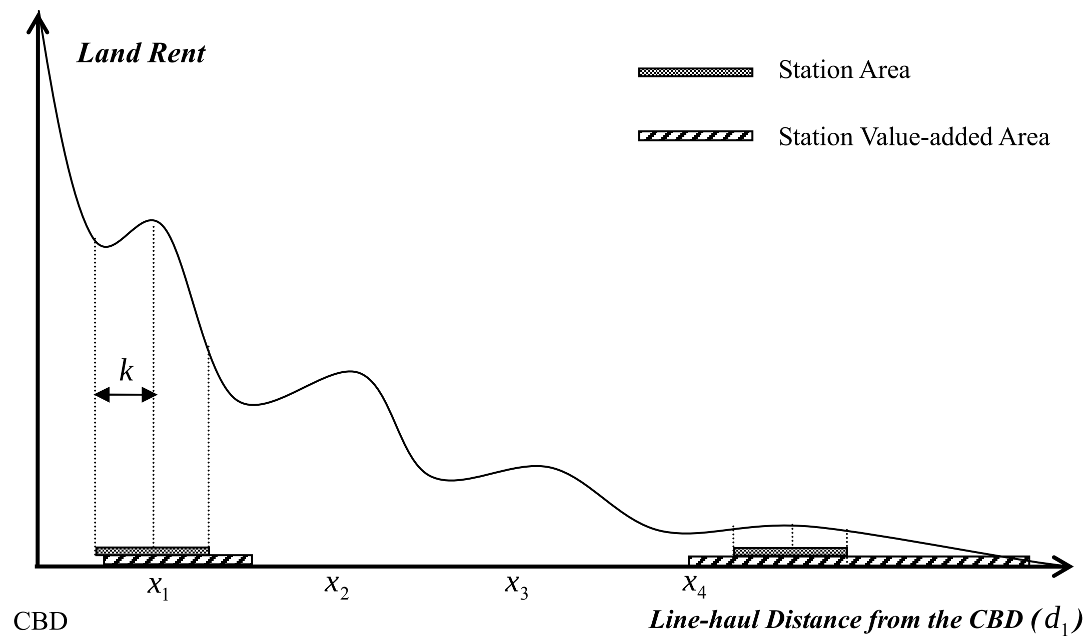

Figure 7. Station Area vs. Station Value-added Area

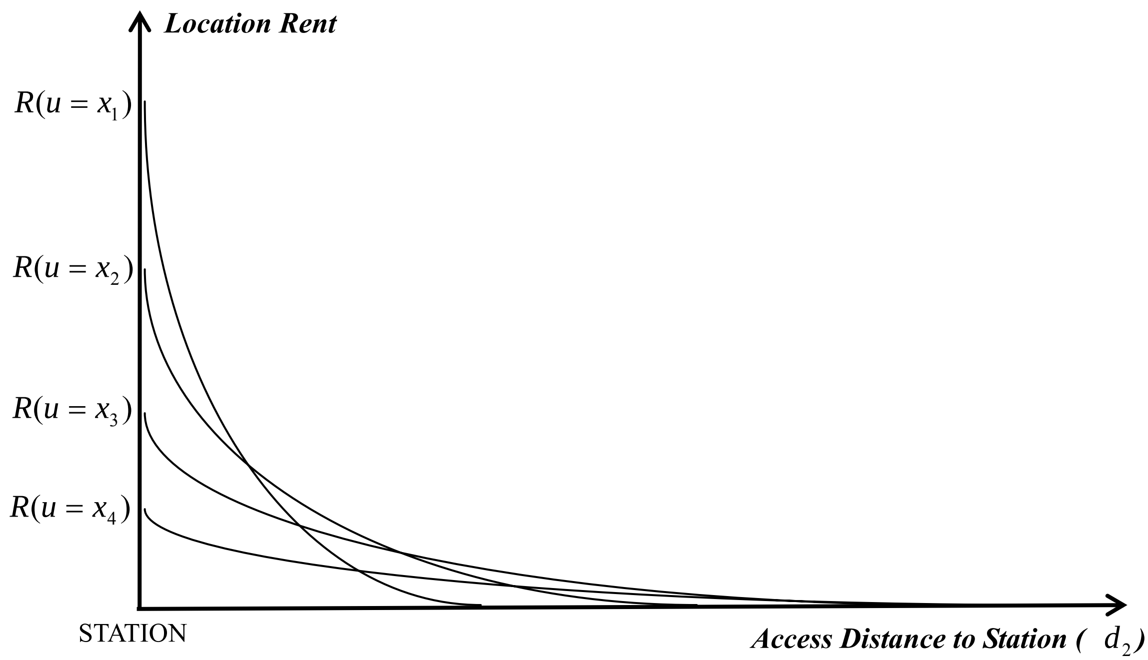

Figure 8. Various Rent Slope for Station Proximity by Location in the City

As seen in Figure 7, station value-added area may not be the same as station area. It has a longer tail at the right side than at the other side. Also, it is wider in the suburbs than in the CBD. Steeper rent slope for station proximity in Formula (10) decreases the boundary of 'station value-added area,' as seen in Figure 8. Thus, the incongruence of station area with station value-added area may be more serious in the area close to the CBD. A research with a dummy variable denoting k has more difficulty in measuring the benefits of erratic stations which distorts the result.

In the basic bid rent model, higher $\partial R / \partial d_2$ in the CBD does not affect the implication that a lower travel cost is more beneficial in the non-urban areas than in the CBD at the early development stage. Thus, the theoretical framework of the study cannot

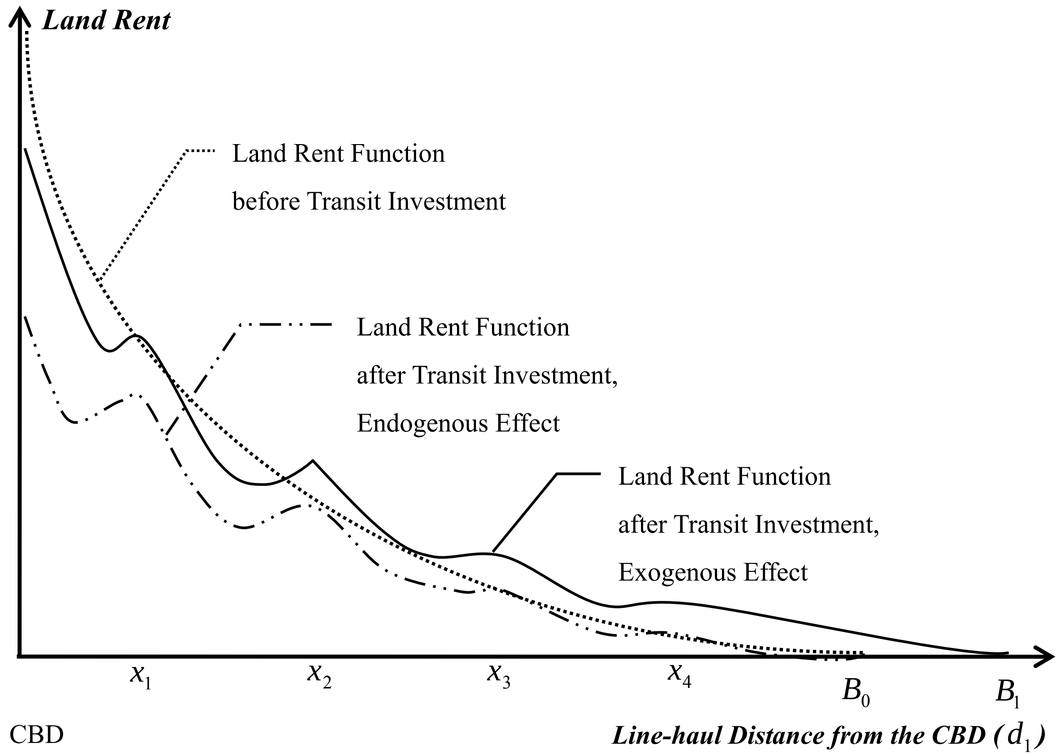

Figure 9. Transit Impact on Land Rent with or without Spatial Constraint

be applicable to the transit's exogenous impact on land use. Figure 9 shows that a lower travel cost reduces the relative importance of the CBD and increases that of the suburbs. However, the economic benefits of station remain higher in the CBD because of the endogenous transit impact on built up urban areas.

Discriminant Transit Impact on Land Rent by Development Density

Another critical location factor is development density in station area. As reported in a study by Nelson (1999), commercial property values are influenced by land use policy encouraging higher development of station areas. With the basic land rent model which assumes an even density distribution, only a brief illustration is possible concerning the influence of development density on the capitalization of travel cost. Let us transform land rent in Formula (1) is a rental ($R(u)$) comprising land rent (L) and structure rent (S) with development density of D. Then, $R(u)$ can be rewritten as follows:

(30) $$R(u) = \frac{L(u)}{D} + S$$

Suppose any other assumptions still hold, then new land rent gradient and $\partial L / \partial d_2$ can be defined as follows:

(31) $$\frac{\partial L}{\partial u} = -\frac{tD}{H(u)}$$

(32) $$\frac{\partial L}{\partial d_2} = -\frac{tD}{H(u)} \times \frac{\partial u}{\partial d_2} = -\frac{tD}{H(u)} \times \frac{d_2 + d_1 \cos\theta}{u}$$

As development density goes up evenly all across the city, land rent gradient increases as much as D times. So does rent slope for station proximity. However, this approach is applicable only when D represents an average of a city, e.g. in a comparative study. All Formula (32) can say is that transit impact on land value is more easily capitalized in a denser city. When density is a function of u, i.e. $D(u)$, no further explanation is ventured with land rent model by travel cost.

Nonetheless, if a station area is assumed to be an independent unit like a city, the capitalization of station proximity becomes steeper in a denser station area than in a less developed one due to the multiplier effect of density with travel cost of accessibility to station, i.e. $\partial L / \partial d_2 = (\partial L / \partial u) \times (\partial u / d_2)$. When it is assumable that the land gradient is heightened by development density, $\partial L / \partial d_2$ becomes steeper with higher density.

Modeling Discriminant Transit Impacts by Location in the City and by Density

The non-linearity concerning the capitalization of station proximity with increasing distance from the CBD can be delineated in Figure 6. Momentous rent gradients differ greatly by location in the city, though they have equal distance from station, e.g. $\left[\frac{\partial R}{\partial d_2}\right]_{d_1=x_1+d_2}$, $\left[\frac{\partial R}{\partial d_2}\right]_{d_1=x_2+d_2}$, $\left[\frac{\partial R}{\partial d_2}\right]_{d_1=x_3+d_2}$ and $\left[\frac{\partial R}{\partial d_2}\right]_{d_1=x_4+d_2}$ at locations d_2 away from stations x_1, x_2, x_3 and x_4. Since the price elasticity to accessibility to station ($\partial R / \partial d_2$) for commercial use is higher than that for residential use (Damm et al., 1980), commercial rentals are expected to be more sensitive to station proximity in the CBD than in the suburbs. Significantly different rent slopes by location in the city raise two research questions: one is the validity of assumption of a single rent slope on station proximity ($\partial R / \partial d_2$), the other is the spatial autocorrelation in the OLS residuals.

As seen in Figure 10, the hedonic model assumes that only one single regression coefficient ($\partial R / \partial d_2$ or $\beta_{Station}$) exists across a city. It makes the equation look simple but ignores discriminant transportation demands from various locations in city. In a city where the substitution effect exists as in Formula (22), the $\beta_{Station}$ decaying with increasing u should also be conceptualized to capitalize the travel cost discriminately by location in the city. Then, $\beta_{Station}$ is also assumed as a function of u. Statistically, an interaction term ($u \times d_2$) can be added to diagnose the functional relationship between two measures. Extending the conceptual model into a polycentric city with a subcenter, the $\beta_{Station}$ is illustrated both by d_2 and distance from business centers, as seen in Figure 11. The dependent variable, rent, and the $\beta_{Station}$ in any location in the city can

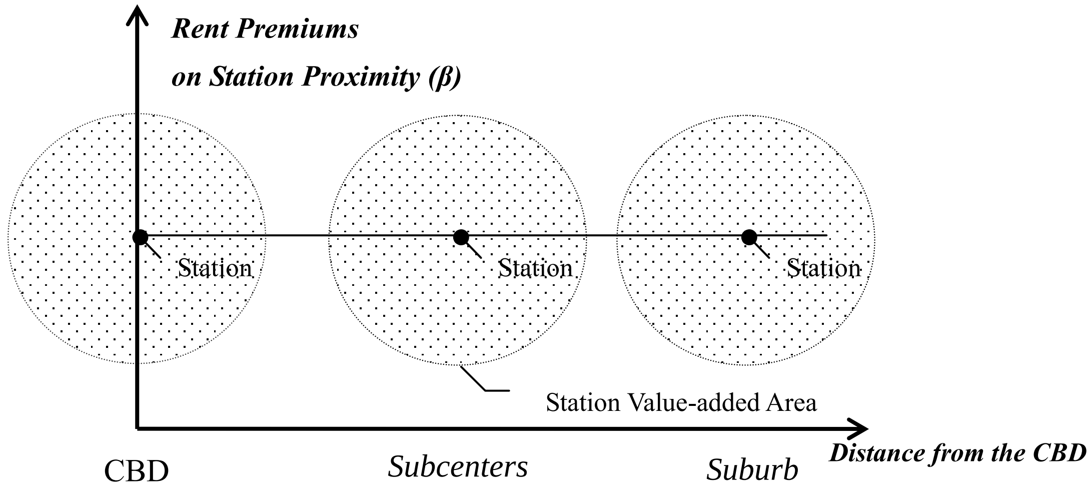

Figure 10. Single Regression β on Station Proximity across the City

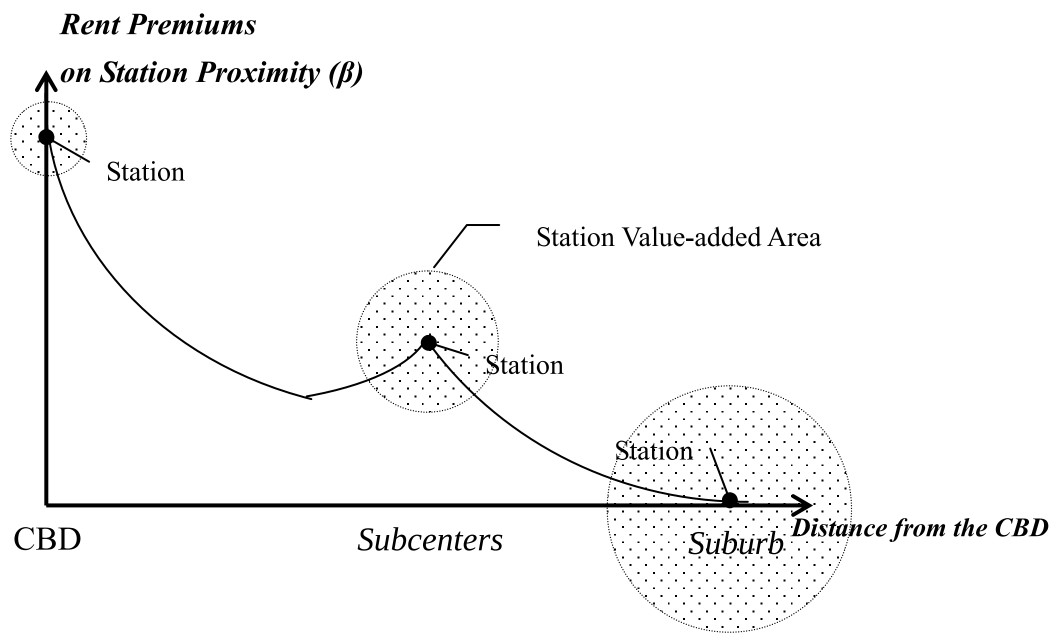

Figure 11. Various Regression βs on Station Proximity in a Polycentric City

be obtained with the equation form as follows:

$$R = \beta_0 + \cdots\cdots + \beta_{DSTA} X_{DSTA} + \beta_{DCEN} X_{DCEN} + \beta_{DSTA \times DCEN} X_{DSTA \times DCEN} + \cdots\cdots + \varepsilon \tag{33}$$

(34) $\beta_{Station} = \beta_{DSTA} + \beta_{DSTA\times DCEN} X_{DSTA\times DCEN}$

where X_{DSTA} and X_{DCEN} denote distance from station and distance from a center, e.g. the CBD or a subcenter, respectively. $X_{DSTA\times DCEN}$ is the interaction between X_{DSTA} and X_{DCEN}. If $\beta_{DSTA\times DCEN}$ shows a positive sign, the $\beta_{Station}$ decays with increasing distance from a business center due to the substitution effect. A study with the CBD-oriented sample would get a significant and high value of coefficient on station proximity, or vice versa.

A counter explanation regarding $\beta_{Station}$s by location in the city may come from misunderstanding of the interaction between d_1 and d_2 in Formula 22. Actually, the non-linear capitalization of station benefits and the interaction between d_1 and d_2 occur simultaneously as d_1 increases, which makes it difficult to discern one from the other. However, as seen in the formula, the numerator ($t(d_2 + d_1 \cos\theta)$) increases linearly but the denominator ($H(u) \times u$) increases geometrically. Net result is the rapidly decreasing capitalization of station proximity. Thus, the decreasing $\beta_{Station}$s by distance from the CBD primarily attributes to the substitution effects of rent gradient function. The 'interaction' term in Formula (22) is not referred to any more.

Another approach regarding various $\beta_{Station}$s by location in the city is the the existence of submarkets disaggregated with travel cost, specifically accessibility to station. Still far, research model assumes a single market differentiated by distance from the CBD and by different-sized units of homogeneous offices. Typical submarket models have focused on differential hedonic prices across metropolitan areas, and the existence of submarkets is believed to attribute to spatial differences in structure and site characteristics, location features and neighborhood amenities. In housing studies, segregation due to race or income may also be an important factor for market segmentation (Vandell, 1995). Various structure and site characteristics may not be substitutes because the costs of transforming one into another is not negligible and location and neighborhood amenities are not easily replicated (Goodman et al., 1998). Thus, for office demanders all the offices across metropolitan areas may not be substitutes.

The differentiation of $\beta_{Station}$ s by location in the city implies that the real estate market is segmented regarding accessibility to transit station, a location attribute. This study applies a methodological concept of Can (1992) to market segmentation regarding transit impact. Her spatial autoregressive study in segmented housing market extended the traditional hedonic model to include the interaction between structure attributes and neighborhood quality scores in the model as follows (p. 459):

$$P = \alpha + \rho WP + \sum (\beta_{k0} + \beta_{k1} NQ) S_k + \varepsilon \qquad (35)$$

where P, NQ and S_k denote the single-family housing prices, the neighborhood quality score and the vector of structural characteristics, respectively. In her study, W is the weight matrix for nearby dependent values and ρ is the coefficient estimate for the first-order spatial autoregressive term.

This study compares the $\beta_{Station}$ in a submarket i with other $\beta_{Station}$ s in other submarkets using the interactions between $\beta_{Station}$ and location dummies (X_{Li}), which takes a spline function form as follows:

(36) $$R = \beta_0 + \cdots\cdots + \beta_{DSTA} X_{DSTA} + \beta_{L_i} X_{Li} + \beta_{DSTA \times Li} X_{DSTA \times L_i} + \cdots\cdots + \varepsilon$$

(37) $$\beta_{Station} = \beta_{DSTA} + \beta_{DSTA \times L_i}$$

where X_{Li} is a dummy variable denoting submarket i. It assumes a hierarchal distribution of $\beta_{Station}$ s by location in the city: the absolute value of $\beta_{Station}$ in the CBD is the highest; subcenters are the second highest and suburbs are the lowest, which can be rewritten as follows:

(38) $$\left|\beta_{StationInCBD}\right| > \left|\beta_{StationInSubcenter}\right| > \left|\beta_{StationSuburb}\right|$$

where $\beta_{StationInCBD}$, $\beta_{StationInSubcenter}$ and $\beta_{StationInSuburb}$ value or rent premium over accessibility to subway stations in the CBD, subcenter and suburbs, respectively. Related to study area, Seoul, Yuh et al. (2002) reports counter evidence to Formula (38). In their study, separate regression coefficients show that $\beta_{Station}$ s are higher in subcenters than in the CBD. However, separate regression approach is not desirable because it implicitly assumes different population parameters of submarkets in a single city.

The dependency of $\beta_{Station}$ on development density similar to Formula (32) is also tested with the same scheme of Formulas (36) and (37) as follows:

(39) $$R = \beta_0 + \cdots\cdots + \beta_{DSTA} X_{DSTA} + \beta_{Den} X_{Den} + \beta_{DSTA \times Den} X_{DSTA \times Den} + \cdots\cdots + \varepsilon$$

(40) $$\beta_{Station} = \beta_{DSTA} + \beta_{DSTA \times Den} X_{DSTA \times Den}$$

where $X_{Density}$ is the development density in station area. Since density is believed to influence the $\beta_{Station}$ by multiplying land rent and station proximity, this interaction is diagnostic for the functional relationship between $\beta_{Station}$ and development density. When $\beta_{DSTA \times Den}$ is positive, rent premiums over station proximity ($\partial R / \partial d_2$) are higher in more developed areas than in less developed ones.

Spatial Autocorrelation in the OLS Residuals

Since the spatially uneven variances of station benefit ($\sigma^2_{\left[\frac{\partial R}{\partial d_2}\right]}$) can be primarily attributed to location in the city, σ^2 may also be influenced by other factors of accessibility and neighborhood amenities. In the presence of spatial autocorrelation, a property value is spatially dependent upon values of nearby properties and the residuals in the hedonic model are spatially autocorrelated.

Spatial autocorrelation is a regression problem where the OLS error terms show, by location of observations, a variance pattern more similar to nearby residuals than those far away. The validity of the OLS cannot be guaranteed because it exists only when it satisfies the error term assumptions of the Gauss-Markov theorem (Gujarati, 2003, pp. 107-12). First, that the expected value of error term corresponding to any explanatory variable is zero, which is denoted as follows:

(41) $$E(\mu_i \mid X_i) = 0$$

The second is the assumption of no serial correlation or no autocorrelation between the error terms. Each error term is not correlated with one another, which is expressed as follows:

(42) $$Cov(\mu_i, \mu_j) = E[\mu_i - E(\mu_i)][\mu_j - E(\mu_j)] = E(\mu_i, \mu_j) = 0 \qquad (i \neq j)$$

The third is the assumption of identically distributed error terms, so-called homo-scedasticity or equal variance or equal spread. Error terms have the equal variances regarding any value of X_i, which can be denoted as follows:

(43) $$Var(\mu_i \mid X_i) = E[\mu_i - E(\mu_i)]^2 = E(\mu_i^2) = \sigma^2$$

The other is the assumption of no correlation between error term and any explanatory variable, X_i. This condition is automatically fulfilled when Formula (41) holds, i.e. X_i is nonrandom or nonstochastic, which can be rewritten as follows:

(44) $$Cov(\mu_i, X_i) = E[\mu_i - E(\mu_i)][X_i - E(X_i)] = 0$$

A linear model which satisfies these four assumptions is so-called the classical regression model or the standard regression model or the general linear regression model (Gujarati, ibid, pp. 108-9). The OLS estimates are the best linear unbiased estimators (BLUE) with desirable statistical properties, e.g. unbiasedness, minimum variance and consistency. Unbiasedness means that a coefficient estimator, $\hat{\beta}$, is equal to the true population parameter, β. Also, when the $\hat{\beta}$ has the minimum variance among all linear unbiased estimators, it is called an efficient estimator. Consistency is a tendency for the $\hat{\beta}$ to converge to its true population parameter, β, as the sample size increases.

The consequences of spatial autocorrelation and unequal variances are almost the same: the OLS estimators are still unbiased but inefficient, i.e. no longer minimum variance estimators, which widen the confidence intervals of coefficients ($\hat{\beta}$). Also, the estimated mean sum of squares due to errors (MSE: σ^2) tends to underestimate the true MSE, which inevitably overestimates the R^2 (Gujarati, ibid, pp. 441-52)[4 and 5] and

4 The formula for the variance of an OLS coefficient is denoted as follows:

weakens the significance tests, e.g. t-, F - and χ^2 tests (Neter et al., 1996, pp. 497-8).

Therefore, the presence of spatial autocorrelation renders the conclusion based on the traditional econometric and statistics problematical. Inefficient estimators can lead a researcher to incorrect conclusions. More seriously, in the presence of spatial autocorrelation, the prediction errors are clearly inflated (Dubin, 1998), which makes the OLS improper for predicting property values. This potential research risk was demonstrated by Wiltshaw (1996) who compared the differences between the hypothesized properties' market prices and estimated values. His map of error terms proved that it is quite possible to obtain statistically significant results even in the presence of spatial autocorrelation.

Modeling Spatial Autocorrelation in Research

In research there are two common ways to reduce the spatial autocorrelation: one is absorbing the dependent variable of nearby properties (SAR: spatial autoregressive model) and the other is inserting the error term directly into the model

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$$\mathrm{var}(\widehat{\beta}_1) = \sigma^2 / \sum_{t=1}^{N} x_t^2$$

Let us assume there is a first-order autoregressive scheme in error terms, i.e. $\mu_t = \rho\mu_{t-1} + \varepsilon_t$ ($-1 < \rho < 1$), then the variance of this estimator will be

$$\mathrm{var}(\widehat{\beta}_1^*) = \frac{\sigma^2}{\sum_{t=1}^{N} x_t^2}\left[1 + \rho\left(\frac{\sum_{t=1}^{N-1} x_t x_{t+1}}{\sum_{t=1}^{N} x_t^2}\right) + 2\rho^2\left(\frac{\sum_{t=1}^{N-2} x_t x_{t+2}}{\sum_{t=1}^{N} x_t^2}\right) + \cdots\cdots + 2\rho^{N-1}\left(\frac{x_1 x_N}{\sum_{t=1}^{N} x_t^2}\right)\right]$$

When ρ is positive, then clearly $\mathrm{var}(\widehat{\beta}_1^*)$ is greater than $\mathrm{var}(\widehat{\beta}_1)$ (Gujarati, 2003, pp. 449-52).

5 Since the R^2 is no more reliable measure under the spatial dependency, the log likelihood ratios can be used to discern the performances of the spatial model from those of traditional hedonic model (Dubin, 1998).

(SEM: spatial error model), or both (SAC: general spatial autocorrelation model or mixed spatial autoregressive model). Using a spatial lag variable provides an economic meaning different from the meaning derived from using spatial error terms. The SAR implicitly assumes that the collective impact of a dependent variable in nearby properties, as well as the explanatory variables, affects each property's value. In contrast, the SEM implies that the omission of one or more key variables makes the errors spatially autocorrelated. It is appropriate when the focus is only to correct the autocorrelation, which enables the equation to produce more efficient estimates and ensures that the inference is correct (Kim et al., 2003, pp. 28-9). The general spatial autocorrelation model, the SAC, which extends the traditional hedonic model to contain both the spatial lag and error variables, is a mixed model of SAR and SEM. It attempts to measure the weighted average of the dependent variable in neighborhood properties and to correct the autocorrelated error structure.

The SAR model extends the traditional hedonic model to include the neighbors' dependent values. Anselin (1988) proposed the maximum likelihood solution for this model which takes the form as follows:

(45)
$$\begin{cases} y = \rho W y + X\beta \quad + \varepsilon \\ \varepsilon \sim N(0, \sigma^2 I_n) \end{cases}$$

where W is spatial weight matrix and ρ denotes a coefficient estimate for the first-order of weighted spatial lag variable. The SEM, labeled by Anselin (ibid), includes the neighboring properties' error terms as well as n number of X variables and takes the form as follows:

$$(46)\qquad \begin{cases} y = & X\beta + \mu \\ \mu = & \lambda W\mu + \varepsilon \\ \varepsilon \sim & N(0, \sigma^2 I_n) \end{cases}$$

where λ is a coefficient estimate for the weighted spatial error terms. The SAC model extends the traditional hedonic model to contain both the spatial lagged variables and the spatial error terms, which takes the form as follows:

$$(47)\qquad \begin{cases} y = & \rho W_1 y + X\beta \quad + \mu \\ \mu = & \lambda W_2 \mu + \varepsilon \\ \varepsilon \sim & N(0, \sigma^2 I_n) \end{cases}$$

where W_1 and W_2 are spatial weight matrices for the spatial lag variable and error terms, respectively. In Formula (47), sometimes W_1 can be equal to W_2, but in that case there may be an identification problem. In this study, W_2 is contrived as $W_1' \times W_1$, following LeSage's text (1998, p. 61). Formula (47) also makes it possible to arrange the relationships between estimation models. When both ρ and λ are zeros, it becomes the same as the OLS estimation. When ρ is zero but λ is not, then the model becomes the SEM model. In contrast, when λ is zero but ρ is not, the estimation is equal to the SAR estimation.

Chapter Summary

In the basic bid rent model, a new transportation investment is expected to reduce travel costs, which lowers the collective level of land rent in a spatially constrained city. Travel cost is more rapidly capitalized by a shorter distance to the CBD due to decreasing housing consumption. This tendency also appears in office land rent gradient.

This study shows that accessibility to stations is also capitalized with a non-linear pattern, regardless of the concept of distance and travel pattern. This capitalization contains not only the net economic benefit of station proximity but also its interaction with line-haul benefits. The relative importance of the latter increases as the line-haul distance almost approximates the total travel distance. Residents in the suburbs pay higher dollars in a station area not for the net station benefit but for line-haul time savings. Thus, station proximity is not a motivation for their location any longer. Also, the station's value-added areas become narrower in the suburbs, which make the station benefits higher in properties orthogonally located to a subway line. Though, these findings do not affect the implication of land rent model that a lower travel cost is more beneficial in a non-urban suburb than in the CBD: the exogenous transit impact on land use change. In built up areas, the economic benefits of station remain higher in the CBD than in the suburbs: the endogenous transit impact on land values.

Problems lies where a poorly specified model in the hedonic approach does not exactly capture the transit impact on land values. It is not easy to capture the line-haul time savings with a poor model specification. Besides, when a sample concentrates on the suburbs, the coefficient of station proximity may be underestimated partly due to the substitution effect and partly due to the narrower station value-added area which let a sample absorb insignificant benefits except in properties orthogonally located to a transit line. The inconsequential impact of station proximity on land value may be found in the city where this economic benefit actually exists. Also, due to the incongruence of station area with station value-added area, using a dummy variable based on walking distance from the station may be intrinsically risky. Since the interval between stations decreases by a shorter distance to the CBD, a poorly defined dummy may measure the economic benefits of other stations. These questions do not belong solely to transit research, but to all the studies on transportation modes which have traffic nodes, e.g. highway ramps.

It is clear that the economic benefits of station proximity are more easily capitalized in a denser city. When a station area is assumable to be an independent unit, the rent slope becomes steeper in a dense station area than a less developed one.

Discriminant transit impact on land value by location and development density raises two methodological questions regarding spatial phenomena: one is differential in the hedonic prices across a single market and the other is the spatial autocorrelation in the OLS residuals. The former can be tested with the functional forms of station benefits correlated with distance from centers and densities and with a submarket approach. By reducing spatial dependency, it is expected to capture a more accurate and efficient parameter estimator for transit's impact on land values.

CHAPTER IV

METHODOLOGY

Model Specification

Traditional Hedonic Model. Literature in property value has considered three main categories of property attributes influencing the property values: structure, location and neighborhood attributes. The hedonic model can be denoted as follows:

$$V = f(S, L, N) \tag{48}$$

where V is the property's market price, S denotes the structural attributes, L represents the location attributes, and N is the neighborhood attributes. And, it takes the equation form as follows:

$$\begin{cases} y = X\beta + \varepsilon \\ \varepsilon \sim N(0, \sigma^2 I_n) \end{cases} \tag{49}$$

The structural category contains such attributes as property age, lot size, floor area, exterior features, and several amenity features. In housing research, amenical features are mainly related to the number of bedroom and bathroom, the size of living room and the dummies of fireplace, garage and air conditioning. Literature on office properties has included such variables as total floor area of a building, property condition (Dunse et al., 2001), building framework, number of elevators, subterranean parking facility (Sivitanidou, 1996 and 1997), carpeting, air conditiontiong, private entrance, security system, tea preparation area, reception area (Dunse et al., 1998), conference room, restaurant, health club (Bollinger et al., 1998) and bank (Lee et al., 2002b). If a study concerns commercial rent, the features regarding tenants and leasing terms are considered for a research model (Webb et al., 1996; Carter et al., 2000).

Location attributes and the economic benefits of property determined by location in the city are primarily correlated with accessibility to other activity loci, e.g. the CBD and subcenters, accessibility to subway or highway, distance to the nearest shopping mall/airport/beach, administrative boundary, school district, and the longitude and the latitude of property (Bollinger et al., 1998; Dubin, 1992; Pace et al., 1997; Can, 1992; Basu et al., 1998; Goodman et al., 1998). Research regarding retail rentals in shopping malls by Carter et al. (2000) uses distance to the mall center and the nearest mall exit as proxies for this category of variables.

Neighborhood variables are often designed to capture the positive or the negative local characteristics of nearby properties. Housing research has focused on factors determining the quality of residences, e.g. socio-economic status of neighborhood or demographic features (Dubin, 1988; Haider et al., 2000), environmental benefits or pollution (Kim et al., 2003), zoning and crime rates. Literature regarding office rentals has considered not only demographic features (Bollinger et al., 1998), commercial zoning (Sivitanidou, 1996 and 1997) and crime rates in neighborhoods but also local economic conditions, e.g. the regional economic index (Pace et al., 1997) and employment growth (Glascock et al., 1990), concentration of office and business service, e.g. FIRE (financial, insurance and real estate) industries, and location prestige (Sivitanidou, 1996 and 1997). Dubin (1992) and Basu et al. (1998) omitted these attributes and predicted property prices by using error terms or kriging the sale prices of neighboring properties. Carter et al. (2000) used distance to the nearest same type store and the nearest vacant store as proxies for this category of variables.

Variables and Measurements

Dependent Variables and Their Measures. The dependent variables are each property's office rent per leased area ($\$/m^2$) and appraised land value per unit ($\$/m^2$). Since the land value is not believed to respond to the physical attributes of a building but to location and neighborhood factors, the estimation for land value does not include structure category variables.

The rent will follow the Chonse value (C), a unique leasing form in Korea, where a tenant lends a large amount of money as the deposit, usually forty to fifty percent of the value of the space to be occupied. Instead, the tenant will not pay monthly rent during occupancy and take the deposit back when he moves out. Usually the owner uses this money to finance the property or rolls it over for more capital gain. Related to all types of properties, this leasing form is used as the basis for calculating monthly rents. Various combinations of monthly rent (R) and deposit (D) can be converted to C with the conversion rate (i). If C follows the market value and D is set with a contract, R can be calculated with the monthly conversion rate ($i/12$) multiplied by the difference between C and D. It can be rewritten as follows:

(50) $$R = (C - D) \times \frac{i}{12}$$

Besides numerous combinations of R and D, there is another rationale for using Chonse value instead of monthly rent: the spatial variances of conversion rates which are volatile across submarkets and vary from contract to contract. Research by Choi et al. (2002) reports that the smaller the tenant's capital the higher the rate required. Also, as the capital size of owner and the building age increase, the rate tends to decrease.

Independent Variables and Their Measures. Two estimation models are designed to test the research questions in the theoretical framework: Model 1 examines the influences of substitution effect and development density using the interactions of accessibility to station and location attributes, e.g. distance from the CBD and subcenters and development densities of station areas. Model 2 verifies the existence of submarkets regarding station proximity. Thus, the structure and the neighborhood categories are common in both models, while the location and the interaction categories differ by purpose of models. Table 1 shows both the dependent and independent variables used in the estimation.

The structure category contains such variables as building age (BAGE), total floor area of a building (FLAR), number of underground floors (BASE), leasing term (TERM, dummy variable if it is a Chonse contract) and bank tenant on the property (BANK, dummy variable if there is any bank. See more in Appendix). The expected signs for the coefficients of BAGE and TERM are negative, while those for the others are positive. BAGE, FLAR, TERM and BANK are chosen based on the literature regarding office rentals (Bollinger et al., 1998; Dunse et al., 1998 and 2001; Glascock et al., 1990; Webb et al., 1996; Lee et al., 2002b). Specifically, FLAR has been considered

Variables		Sign	Unit	Description	Data Source
Dependent	Rent	NA	$/㎡	Chonse value of office rent	The SAMS dataset
	Value	NA	$/㎡	Appraised land value of property	Public Appraisal Value by the City of Seoul
Structure*	BAGE	-	Year	Building age	The SAMS dataset
	FLAR	+	㎡	Total floor area of building	The SAMS dataset
	BASE	+	number	Number of underground floors	The SAMS dataset
	TERM	-	0 or 1	1 if the lease contract is Chonse	The SAMS dataset
	BANK	+	0 or 1	1 if the property possess a bank tenant.	The SAMS dataset
Location	DCBD	-	m	Distance to Central Business District	Measure with ARC-View, SDI.***
	DSUB	-	m	Distance to the nearest subcenter	Measure with ARC-View, SDI.
	DSTA	-	m	Walking distance to nearest station	Web-based GIS, www.freemap.net
	CBD**	+	0 or 1	1 if belongs to CBD submarket.	GIS Coordinates, SDI.
	KNM**	+	0 or 1	1 if belongs to Kangnam submarket.	GIS Coordinates, SDI.
	SAM**	+	0 or 1	1 if belongs to Samsung submarket.	GIS Coordinates, SDI.
	YDO**	+	0 or 1	1 if belongs to Yoido submarket.	GIS Coordinates, SDI.
Neighbor-hood	LQFI	+	Index	Locational Quotient of Finc. Inst.'s in local administrative district	2003 Yearly Statistics of 25 Wards in Seoul
	PSRS	+	persons/day	Passenger ridership of nearest station	Seoul Metro. Subway Co., Seoul Metro. Rapid Transit Co. and Korea National Railroad
	ZONE	+	0 or 1	Zoning, 1 if belongs to a commercial area	Public confirmation on land use by City of Seoul
Interaction	STCB	+	m × m/1000	Interaction between DSTA and DCBD	DSTA×DCBD
	STSU	+	m × m/1000	Interaction between DSTA and DSUB	DSTA×DSUB
	STPS	-	m×persons/1000	Interaction between DSTA and PSRS	DSTA×PSRS
	DSTC**	-	m	DSTA in the CBD submarket	DSTA*CBD
	DSTK**	-	m	DSTA in the Kangnam submarket	DSTA*KNM
	DSTS**	-	m	DSTA in the Samsung submarket	DSTA*SAM
	DSTY**	-	m	DSTA in the Yoido submarket	DSTA*YDO
	DSTO**	-	m	DSTA in Other areas	DSTA*Other

*Variables in structure category are used only for rent estimation.

**Variables are used for Model 2, replacing DCBD, DSUB, DSTA, STCB, STSU and STPS. The others are commonly used for Model 1 and 2.

***SDI is the abbreviation of Seoul Development Institute.

Table 1. Variable description and Data Source.

a challenging research variable because it is one of the most critical factors determining the class of an office building, i.e. Class A, B and C, and correlated with the size effect: that is, tenants tend to pay more for larger offices which may supply better services, have more modern equipment, and be more prestigious. Also, there is sufficient rationale to confirm that BASE influences office rentals: a higher BASE is more beneficial for tenants by providing more spacious subterranean parking, other things being equal. Availability of subterranean parking is one of the important structural variables in a study by Sivitanidou (1996).

The location category in Model 1 contains mainly the distance variables, i.e. distance from the CBD (DCBD), from the nearest subcenter (DSUB) and from the nearest transit station (DSTA). All the expected coefficient signs are negative and distance decayed. In Model 2, location dummy variables denoting submarkets, the CBD (CBD), Kangnam (KNM), Samsung (SAM) and Yoido (YDO) are replacing DCBD and DSUB to avoid a possible multi-collinearity problem.

Distance matrix between properties (731×731), DCBD and DSUB are calculated based on the coordinates of properties in ARC-view GIS. Distance between two points, (x_i, y_i) and (x_j, y_j), is calculated as follows:

(51) $$d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$$

DSTA of each property is not direct distance but shortest walking distance from a station measured on a web-based GIS (www.freemap.net).

The neighborhood variables are the location quotient of financial institutions

(LQFI) in the local administrative district, the zoning ordinance for each property (ZONE) and the passenger ridership of stations (PSRS). LQFI is related to the level of business service in the neighborhood which an office property belongs to. This study considered several business services and calculated their LQs based on the number of business entities and the employment size, e.g. the LQ of office entities, the LQ of office employ-ment, the LQ of FIRE (financial, real estate and business service industries) entities, the LQ of FIRE employments, the LQ of financial institutions and the LQ of financial employments. Among all the business service, LQFI based on business indices was consistently significant in regression estimations, which is calculated with the following formula:

(52) $$LQFI_i = \frac{FI_i / TE_i}{FI_S / TE_S}$$

where FI_i and FI_S denote the number of financial institutions in district i and in Seoul, respectively. Also, TE_i and TE_S corresponds to the total number of business entities in district i and in Seoul, respectively.

The Zone variable is a dummy denoting only if a property belongs to a commercial area. In advance, this study tested the impact of all types of zones on rent and land value. Specific zoning categorization causes multi-collinearity problems both in rent and value estimation, instead this study selects only the variable denoting commercial land use because it has the highest bi-variate Pearson's correlation coefficients with RENT and VALUE (See more in Appendix).

The PSRS, a proxy variable reflecting the development intensities of station areas in this study, is the average daily number of passengers departing and arriving at the station nearest a property. There are several reasons for using PSRS as a proxy for development density: (1) the possible incongruence of station value-added area with station area, as seen in Figure 7; (2) unavailability of GIS data regarding land use in Seoul; (3) the relationship between development density and traffic demand. Literature in traffic demand report that the trip generation is influenced by the population, household income and the number of cars per household in residential areas. Traffic demand in an office area is determined by its local employment, location in the city and development density. Since the PSRS is a modal split resulting from traffic volume, it can represent development density of a station area as well as travel propensity.

To test the hypotheses, Model 1 contains the interactions of DSTA with DCBD (STCB), DSUB (STSU) and PSRS (STPS). All the interactions are divided by 1,000 to prevent units too big. In the cases of STCB and STSU, the coefficients are interpreted as changing regression beta on station accessibility ($\Delta\beta_{Station}$) as a property becomes one kilometer away from the centers. Model 2 tests the interactions of DSTA with the location dummies, i.e. CBD (DSTC), KNM (DSTK), SAM (DSTS) and YDO (DSTY).

Detection of Spatial Autocorrelation

This study used four asymptotic statistics, i.e. Moran's I, likelihood ratio (LR), Lagrange Multiplier (LM) and Wald test, to test for spatial autocorrelation in the OLS errors ($H_0 : \lambda = 0$ or no spatial autocorrelation). Moran's I and the LM statistics use the spatial weight matrix W_1 applied to the SAR, while the LR and the Wald statistics are calculated with the W_2 used in the SEM and λ, a maximum likelihood estimate for error term autocorrelation from the SEM. Moran's I for unstandardized asymptotic distribution is calculated with the following formula (Cliff et al., 1973, pp. 92-3):

(53) $$Moran's \quad I = \frac{n}{W}\frac{e'We}{e'e} = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{(\sum_{i=1}^{n}(y_i - \bar{y})^2)(\sum\sum_{i \neq j} w_{ij})}$$

where e and n are the OLS residuals and the number of observations, respectively. The LM statistic is calculated as follows (Anselin, 1988, p. 104):

(54) $$LM = \frac{1}{T}\left[\frac{e'We}{\sigma^2}\right]^2 \quad \sim \chi^2$$

where $T = tr\{(W + W').*W\}$. The LR test uses the difference between the log likelihood for the spatial error model and the log likelihood for the OLS and it is distributed as χ^2, which is calculated with the formula as follows (Anselin, ibid, pp.103-4):

(55) $$LR = N.\left[\ln(\sigma_0^2) - \ln(\sigma_1^2)\right] + 2\ln.\left|I - \lambda W\right| \quad \sim \chi^2$$

where σ_0^2 and σ_1^2 are the MSE s from the OLS and the SEM, respectively. With the same W_2 and λ, the Wald test statistic is calculated as follows (Anselin, ibid, p. 104):

(56) $$W = \lambda^2\left[t_2 + t_3 - \frac{1}{N}*(t_1^2)\right] \quad \sim \chi^2$$

$$t_1 = tr(W.*B^{-1}), \quad t_2 = tr(WB^{-1})^2 \quad \text{and} \quad t_3 = tr(WB^{-1})'(WB^{-1})$$

where $B = (I_n - \lambda W)$. Also, to test if there remains any spatial dependency in the SAR results ($H_0 : \lambda = 0$), the LM statistic on the SAR residuals is calculated with the weight matrices, W_1 and W_2 in the SAC, and the estimated variance of ρ in the SAR (Anselin, ibid, p. 106; Cliff et al., 1973; LeSage, 1998 and 1999).

(57) $$LM = \left(\frac{e'W_2 e}{\sigma^2}\right)^2 \left[T_{22} - (T_{21A})^2 \operatorname{var}(\rho)\right]^{-1} \qquad \sim \chi^2$$

$$T_{22} = tr(W_2.*W_2 + W_2'W_2) \text{ and } T_{21A} = tr(W_2.*W_1.*A^{-1} + W_2'W_1.*A^{-1})$$

where $A = (I_n - \rho W_1)$.

Weight Schemes

This study used three spatial weight schemes: the $k-$nearest neighbor scheme, the neighbors within a distance limit and the distance inverse matrix. All the schemes are based on distance matrix (731×731) between 731 properties calculated from their coordinates. The first scheme includes only k number of nearest neighbor's lag values or errors. This study chooses one nearest neighbor among the possible number of neighbors with the highest uni-variate Moran's I statistics for rent (0.6851) and value (0.8682) (see Figure 12). In the asymmetric patterned weight matrix, the sum of row always becomes one (Dubin, 1998, pp. 309-16). This scheme is easy to be applied in fields and converted to a sparse matrix, which saves much time for estimation (Figure 13).

The distance limit scheme gives an element zero or one divided by the number of properties within a distance limit in a row. In the weight matrix, the sum of row is always one. It takes the following steps: first, one is weighted for all the elements which are within a distance limit, and zeros are weighted for the others (Dubin, ibid, pp. 316-8). Then, divide each row by the number of properties within a distance limit in that row. This modification, similar to the standardization of contiguity matrix, has a rationale: in a metropolitan area, the numbers of neighbors within a distance limit differ significantly

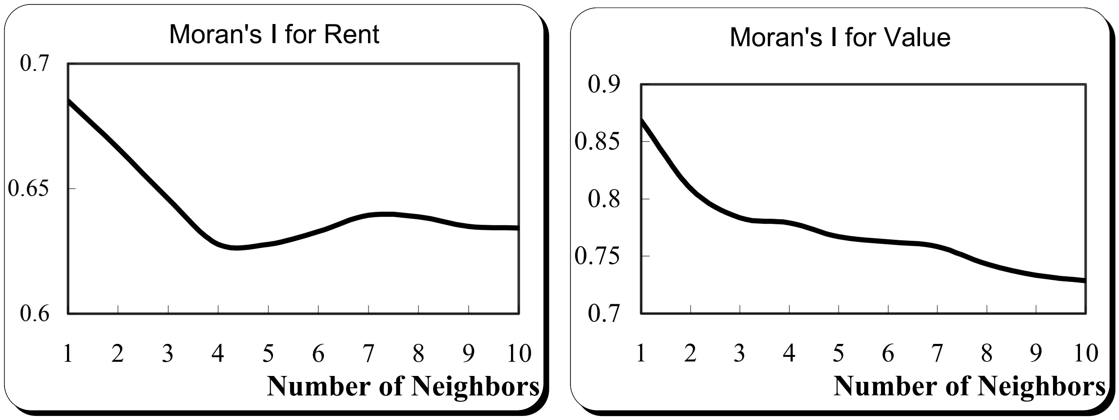

Figure 12. Uni-Variate Moran's I Statistics for the k-Nearest Neighbor Scheme

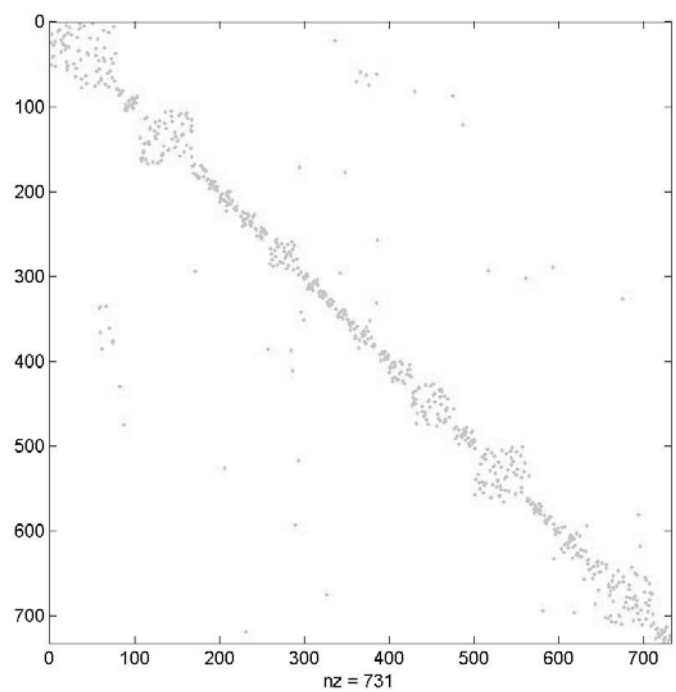

Figure 13. Sparse Distribution of One in Weight Matrix: One Nearest Neighbor

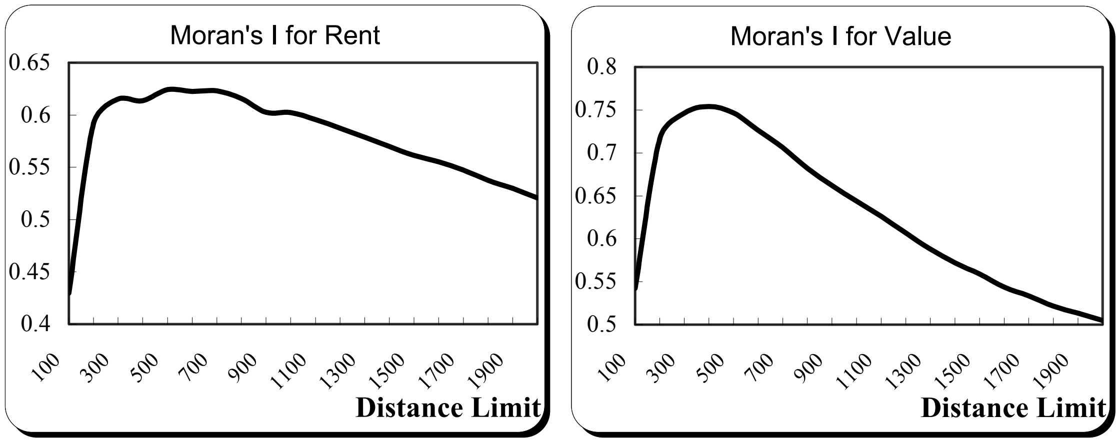

Figure 14. Uni-Variate Moran's I Statistics for the Distance Limit Scheme

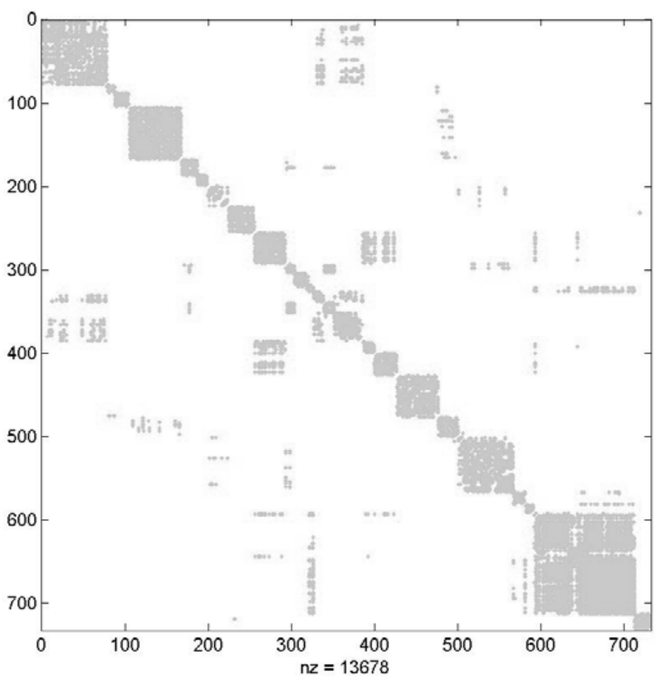

Figure 15. Sparse Distribution of Non-zero in Weight Matrix: Distance Limit

from location to location. There are properties with more than 80 neighbors in the CBD area, while several properties do not have any neighbor in the suburbs. The uneven weights by location in the city may weaken the explanation of spatial variables in the model (LeSage, 1999, pp. 11-4). This study sets up the limit as 500 meters for the rent and as 400 meters for the value estimation because they have the highest uni-variate Moran's Is (0.6244 and 0.7541, respectively) among the possible distance limits (see Figure 14).

The distance inverse scheme inverses all the distances in the weight matrix except the main diagonal, i.e. if $i \neq j$, then $w_{ij} = 1/d_{ij}^{P}$, else $w_{ij} = 0$. This study sets up P as one because all the elements are close to zero in the case where P is more than two. For a study on a large metropolitan area, this scheme may not be proper because most of the elements are not far from zeros, which makes the spatial variables insignificant.

Chapter Summary

The dependent variables are each property's office rent per leased area ($\$/m^2$) and appraised land value per unit ($\$/m^2$). The rent will follow the Chonse value (C), a unique leasing form in Korea. Four categories of property characteristics are considered in the study: structure, location and neighborhood attributes as well as interactions between research variables. However, the estimation for land value does not include structure category variables. This study designs two estimation models: Model 1 examines the interactions of accessibility to station with distance from centers and development densities of station areas, and Model 2 tests the existence of submarkets regarding station proximity using location dummies.

The structure category contains building age (BAGE), total floor area (FLAR), number of underground floors (BASE), leasing term (TERM) and bank tenant on the property (BANK). The location category in Model 1 contains distance from the CBD (DCBD), the nearest subcenter (DSUB) and the nearest transit station (DSTA). In Model 2, location dummy variables denoting submarkets, the CBD (CBD), Kangnam (KNM), Samsung (SAM) and Yoido (YDO) are replacing DCBD, DSUB and DSTA. The neighborhood variables are the location quotient of financial institutions (LQFI), the zoning for each property (ZONE) and the passenger ridership of stations (PSRS). Model 1 includes the interactions of DSTA with DCBD (STCB), DSUB (STSU) and PSRS (STPS). Model 2 tests the interactions of DSTA with the location dummies, CBD (DSTC), KNM (DSTK), SAM (DSTS) and YDO (DSTY).

This study used four asymptotic statistics, i.e. Moran's I, likelihood ratio (LR), Lagrange Multiplier (LM) and Wald test, to test for spatial autocorrelation in the OLS errors ($H_0 : \lambda = 0$). Also, to test if there remains any spatial autocorrelation in the SAR results ($H_0 : \lambda = 0$), the LM statistic on the SAR residuals is calculated with the SAC. Also, it applies three spatial weight schemes to spatial models: the $k-$nearest neighbor scheme, the neighbors within a distance limit and the distance inverse matrix.

CHAPTER V

SITE, DATA AND BASIC DESCRIPTIVES

Site Selection and Description

For three reasons, this study selected Seoul, Korea, as the study area. First, a denser city is more beneficial for measuring the capitalization of station proximity, as seen in Formula (32), Chapter III. Second, for a cross-sectional study on transit's impact on land values it is more desirable that the subway system should be well distributed across the city. Third, the subway system should play a meaningful role in total transportation costs in the city: that is, its share to total passenger trips should be significant.

The population of Seoul was more than 10 million (10,321,449) at the end of 1999. Since its area is around 635 km^2, its gross population density exceeds 163 persons per hectare. If only the net developed area is considered, Seoul's net population density is more than 300 persons per hectare. Currently, the Seoul subway system has eight operating lines and four lines under construction. This system equally serves areas except for development restricted areas as seen in Figure 16. According to actual traffic transportation shares per day in 1999, the subway shared 33.8% of total trips and conveyed more than 4,754 thousand passengers daily. Also, 580 thousand daily passengers used the railway in Seoul (Seoul Metropolitan Government, 2000, pp. 83, 272-3, 280-2 and 286-7).

Data Source

Two main datasets are used in this study; office rents and appraisal land values. The office rent data in Seoul were surveyed by the SAMS Co., Ltd. from October 2002 to November 2003 and served online. The appraisal land values for office properties are based on the dataset annually announced by the Seoul Metropolitan Government (SMG), also available online.

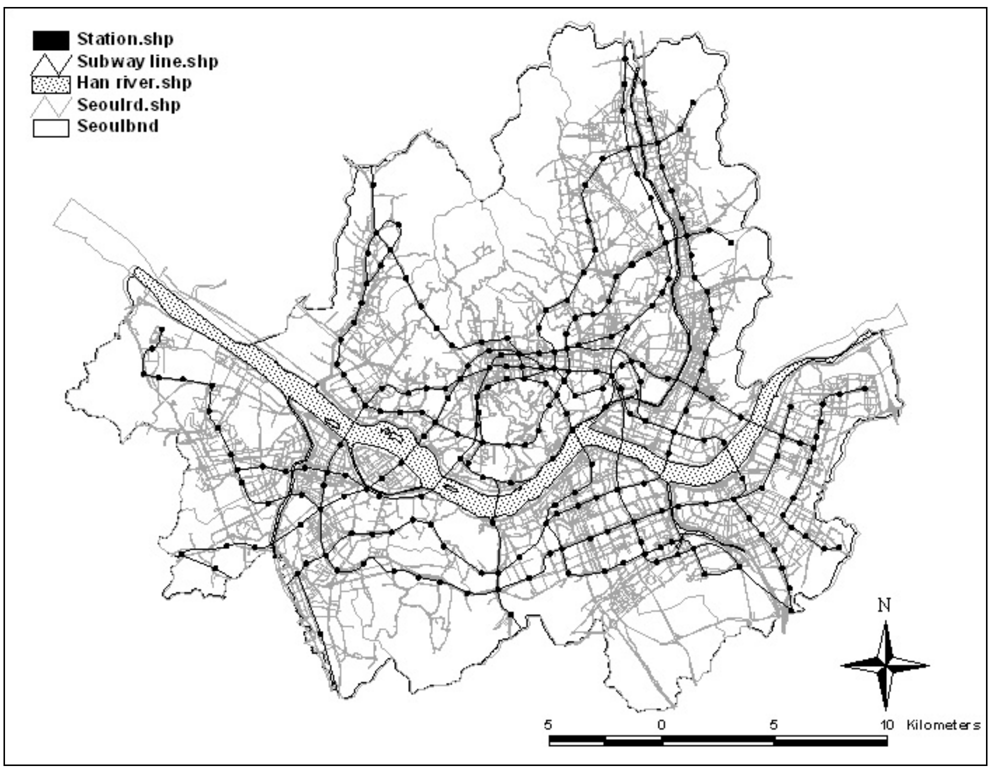

Figure 16. Seoul Metropolitan Subway System

SAMS, formerly Samsung Life Service, manages the Samsung Group's properties throughout the country. The population of its database is primarily based on the list of the Korean Fire Protection Association (KFPA) and is updated every month by surveying 349 sample office rents in Seoul. Currently, this database contains more than 3,000 properties nationwide and more than 1,100 properties in Seoul. It is the most credible database for Seoul office rent and all other datasets are based on its figures. Previous studies, Choi et al. (2002) and Lee et al. (2002a), used it to analyze the cross-sectional office rental structure in Seoul.

Since there is no regulation or consensus discerning the office properties from other buildings in Seoul, it is not easy to suggest any available statistic regarding the total stock of office space. Though, the Ministry of Construction and Transportation defines the commercial properties used for retail or office uses. Except the properties used exclusively for office, most of medium- and small-sized buildings include both uses simultaneously. Instead, there is an indirect measure, the nationwide list of all fire-insured buildings by the Korean Fire Protection Association (KFPA), on which the SAMS dataset is based. By the law, a building more than 10 stories with total floor area more than 35,583 ft^2 (3,306 m^2 or 1,000 pyung) must be insured from fire. Currently, the KFPA defines an office building of which area for office use is more than 70% of total floor area. The SAMS adds around 20% of small buildings in the retail areas, but it evades small ones in local neighborhoods.

This study selected 731 property rentals with the entire leasing information converted to Chonse value. From Formula (50), monthly rent is converted to Chonse value as follows:

(58) $$C = D + \frac{12R}{i}$$

The SAMS dataset has three categories of property information: structure and location attributes and leasing terms. Structure category contains information regarding building name, property age, address, total floor area, lot size, height, efficiency ratio, structure, parking space, number of elevators and heating and air conditioning system. Location category gives brief information regarding transportation and surrounding area of a property. Leasing attributes are gross leased area (GLA), net leased area (NLA), deposit amount, monthly rent, monthly management fee, interest rate to convert monthly rent to Chonse value, survey date, and current owner and anchor tenants.

The structure category of properties in this study mainly comes from the SAMS dataset, while the location category originates from geocoding ARC-View GIS and the neighborhood attributes stem from annual public statistics. The source of the base map for geocoding ARC-View GIS is Seoul Development Institute, a research institute founded and owned by the Seoul Metropolitan Government. The DSTA of each property is the shortest walking distance from a station directly measured on a web-based GIS map site (www.freemap.net).

The LQFI is calculated for 635 local administrative districts based on the 2003 Yearly Statistics of 25 Gu's in Seoul.[6] The PSRS comes from the 2003 Yearly Statistics of subway institutions, i.e. Seoul Metropolitan Subway Corporation, Seoul Metropolitan Rapid Transit Corporation and Korea National Railroad. The Zone is based on the public confirmation on land uses by the City of Seoul and served online.

6 Gu is an administrative unit which only exists in several metropolitan cities in Korea. It is equivalent to the concept of 'Ward' in the U.S.

Seoul Office Submarkets

All the studies on the Seoul office market disaggregated it into three submarkets, i.e. the CBD area, the Kangnam and the Yoido, as seen in Figures 17 and 18. The CBD submarket, located at the center of Seoul encompassing Jongro-gu and Jung-gu has existed since Seoul became the capital of Korea in 1392. The other two submarkets have grown as the result of economic development in Korea and the policies of the City of Seoul to disperse urban functions during the 1970s and 80s. These submarkets are located seven to nine kilometers (about 4.5 to 5.5 miles) away from the CBD. The Kangnam submarket, covering mainly Kangnam-gu and recently expanding to Socho-gu, has grown rapidly. The Yoido submarket, located at the mid-western part of Seoul,

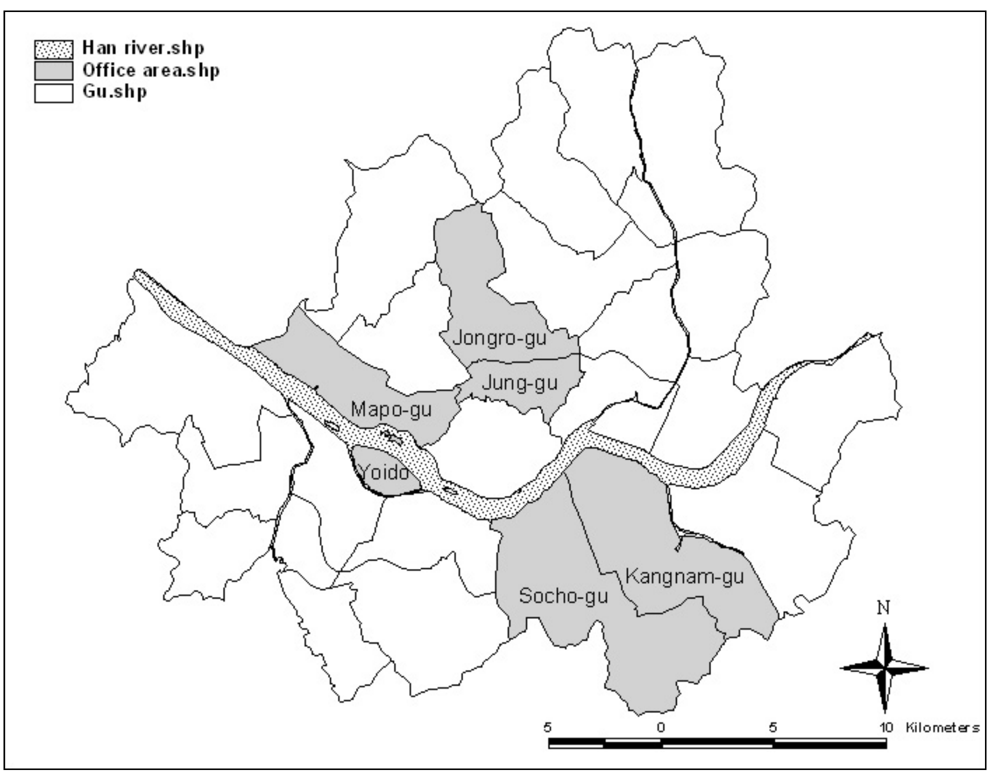

Figure 17. Submarket Disaggregation by Previous Studies

covers Mapo-gu and Yoido-dong in Yongdeungpo-gu.

The disaggregation scheme used by previous studies makes a research easy and quick because all a researcher has to do is to obtain the addresses of properties. No need for geocoding the data or measuring distance from centers. However, it is theoretically problematic: literature on the office submarket report that the radius of a business center does not exceed around one mile or 1.6 kilometers. The sum of submarket areas by this scheme is around one sixth of total city area. This study sets the radius of a business center as 2.0 kilometers for every submarket in which each nuclei is the property with the highest appraised land value. The reason for a radius slightly wider than one mile is to secure a degree of freedom for coefficient estimates in Model 2 using location dummy

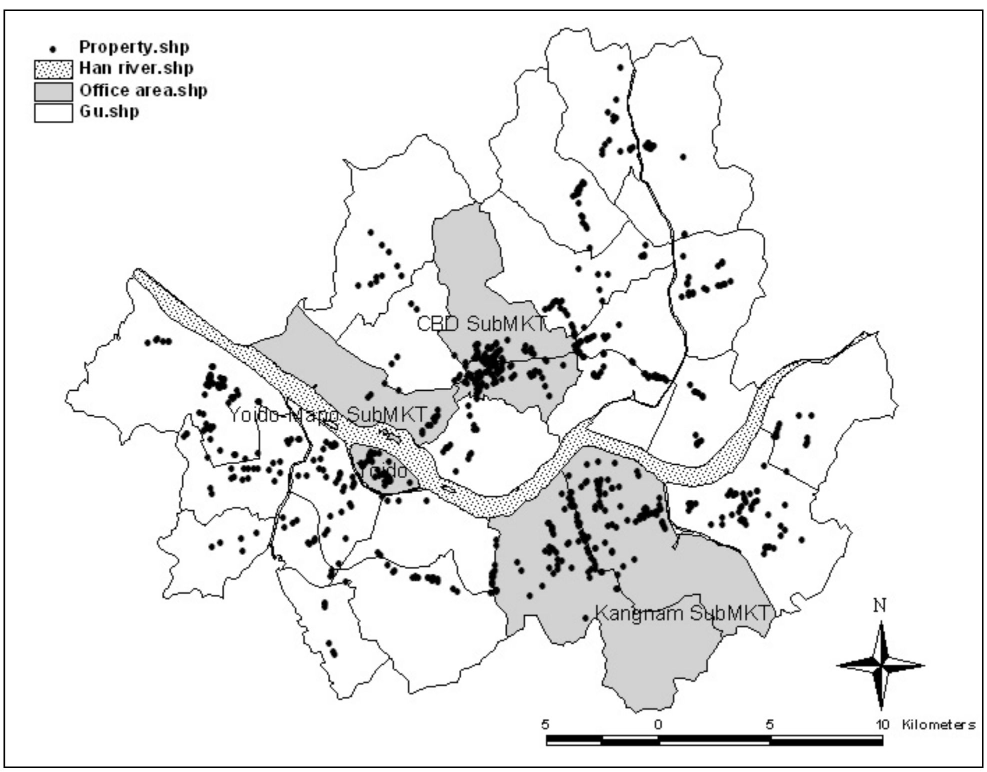

Figure 18. Distribution of Surveyed Data by Disaggregation of Previous Studies

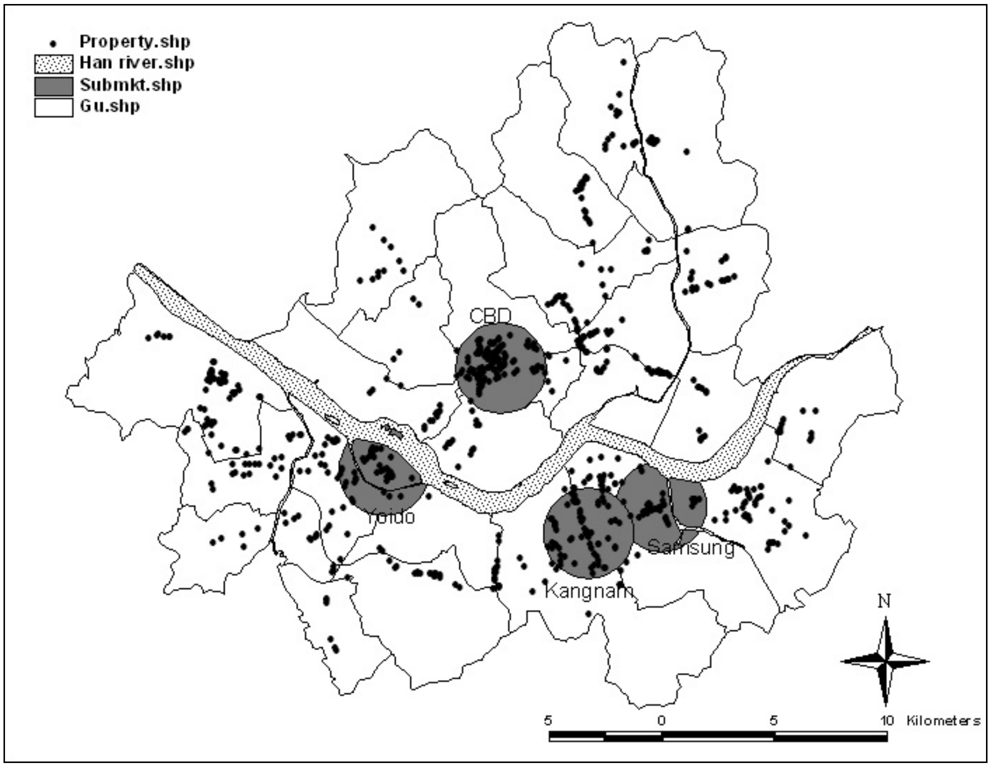

Figure 19. Adjustment of Submarket Disaggregation in Seoul

variables. The study also divides the Kangnam area into two submarkets, the Kangnam submarket and the Samsung submarket, as seen in Figure 19. With different development histories, these two areas are not considered to be homogeneous regarding their urban economic activities. Also, these areas are so dispersed that one location dummy may not absorb all the local characteristics.

119 properties belong to the CBD submarket, 67 properties to the KNM, 33 properties to the SAM and 47 properties to the YDO, respectively. Dispersed widely all across the city, 465 properties do not belong to above submarkets. The surveyed data above the Han River and in the southwestern part of Seoul are located along main artery roads which extend outward from the CBD. Offices in the southeastern part are widely

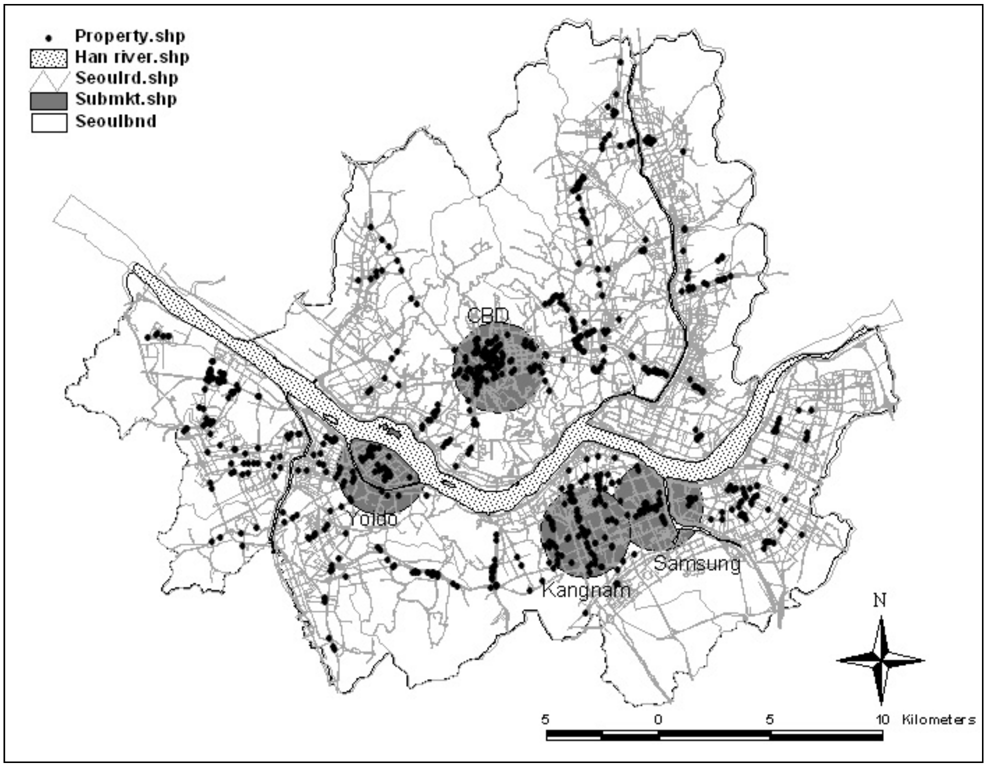

Figure 20. Distribution of the Surveyed Data along the Street System

distributed along the grid pattern street system which makes it difficult to find the central point (See Figure 20).

The surveyed properties tend to be located near the stations, particularly in the CBD, KNM and SAM submarkets, as seen in Figure 21. However, since the subway lines in Seoul are to be built on the main artery roads, it can hardly be determined whether this pattern is attributed to transit accessibility or not. It is notable that the distance to stations seems to increase the farther away a property is from the CBD.

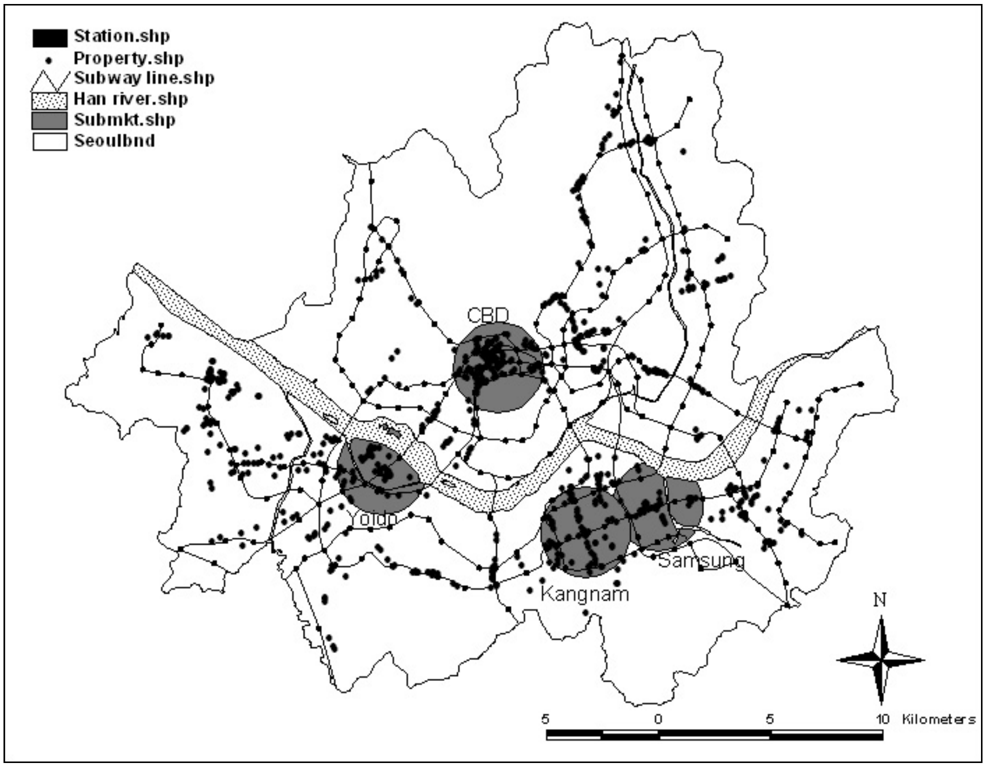

Figure 21. Distribution of the Surveyed Data along the Subway System

Descriptive Statistics of Surveyed Properties

As seen in Table 2, descriptive statistics of surveyed data, the average rent and appraisal value in the CBD are the highest among the submarkets and those in subcenters are the next. Reflecting the different development eras in submarkets, the average BAGE of the CBD is the largest; those of the YDO, the KNM and the SAM submarkets are the second largest. Related to building size, the average floor area and the number of elevators in the CBD are the highest, while those in the YDO, the SAM and the KNM are next. The average number of underground floors in the CBD is the greatest; with those in the SAM, the KNM and the YDO following in descending order. The average TERM of submarket shows a clear pattern: property owners in recently developing areas, e.g. KNM, SAM and other areas, prefer the Chonse contract to a monthly rental one. Besides, properties in the CBD submarket have a higher rate for a bank tenant to reside in.

Properties in the CBD have the best transit accessibility, while those in the YDO with only two stations have the poorest. The offices in the KNM and the SAM submarkets seem to be located within station areas. The location quotient of financial institutions, a proxy for the business service level, shows that these institutions are concentrated in the CBD and the YDO submarkets. The average passenger ridership in

Submarket			Total	CBD	KNM	SAM	YDO	Other
Sample Size			731	119	67	33	47	465
Dep-endent	Rent	Mean	899	1605	922	913	903	713
		St Dev	466	622	302	244	305	232
	Value	Mean	4833	9773	6904	6766	3744	3243
		St Dev	3708	5130	2723	3747	1682	1686
Stru-cture	BAGE	Mean	12.51	16.90	13.03	11.30	15.28	11.12
		St Dev	6.41	9.66	5.45	4.03	5.65	4.95
	FLAR	Mean	13767	32600	11158	15014	22112	8392
		St Dev	19480	26045	8296	14715	33668	12622
	BASE	Mean	2.87	4.08	3.46	3.79	3.40	2.35
		St Dev	1.73	1.79	1.52	1.69	1.44	1.53
	TERM	Mean	0.58	0.08	0.82	0.67	0.23	0.70
		St Dev	0.49	0.27	0.39	0.48	0.43	0.46
	BANK	Mean	0.37	0.61	0.49	0.39	0.34	0.30
		St Dev	0.48	0.49	0.50	0.50	0.48	0.46
Loca-tion	DCBD	Mean	7679	947	8102	9332	7197	9273
		St Dev	4095	484	990	837	737	3415
	DSUB	Mean	5839	6848	1247	901	942	7088
		St Dev	3875	778	508	607	539	3788
	DSTA	Mean	399	214	369	422	597	429
		St Dev	378	138	264	208	358	425
Neig-hbor-hood	LQFI	Mean	1.81	3.03	1.67	2.60	3.23	1.32
		St Dev	1.50	1.91	0.71	1.30	1.33	1.18
	PSRS	Mean	62830	83274	99863	108119	56744	49663
		St Dev	39631	26367	51123	52414	30592	31805

Table 2. Descriptive Statistics of Surveyed Data

the SAM and the KNM is the highest, while those in CBD, YDO and other areas are next. Since the CBD area is better served with more subway lines and stations, the average ridership for each station in the CBD area is lower than that in the two subcenters.

Chapter Summary

This study uses two datasets: office rents and appraisal land values. The office rent data originates from the SAMS Co., and the appraisal land values are announced by the City of Seoul. This study selected 731 property rentals with the entire leasing information converted to Chonse value. The structure, location and neighborhood attributes in the study stems from the SAMS dataset, GIS data and public statistics, respectively.

This study disaggregates the Seoul office market into four submarkets, i.e. the CBD area, the Kangnam, the Samsung and the Yoido of which radius is 2.0 kilometers, each. 119, 67, 33 and 47 properties belong to each submarket and 465 properties do not belong to above submarkets. The surveyed properties tend to be located near the stations, particularly in the CBD, KNM and SAM submarkets. The CBD area is better served with more subway lines and stations than the other submarkets.

The average dependent values in the CBD are the highest among the submarkets and those in subcenters are the next. The average BAGE of the CBD is the largest; those of YDO, KNM and SAM submarkets are the second largest. The average FLAR and BASE in the CBD are the highest, while those in YDO, SAM and KNM are next. A monthly rental is common in the CBD submarket, while the traditional Chonse contract is dominant in newly developing submarkets, e.g. KNM, SAM and other areas. The average BANK in the CBD is highest among submarkets. The LQFI in the CBD and the YDO submarkets are higher than the others. The average PSRS in the SAM and the KNM are the highest, while those in CBD, YDO and other areas are next.

CHAPTER VI

ANALYSIS RESULTS

The basic hedonic model is estimated by the OLS method while the spatial models like SAR, SEM and SAC are estimated by the maximum likelihood (ML) method using MatLab 6.1 matrix functions contributed by LeSage and other academicians.[7] Since under the spatial autocorrelation the R^2 and $Adj-R^2$ from the OLS model is not credible any longer, the model performances are delineated with the log-likelihood rates and the MSE s.

Estimation Results with Model 1

Tables 3 and 4 show the regression results on rent and value. In the structure category, only the total floor area of building (FLAR) seems significant and shows expected positive signs, regardless of model types. Tenants tend to pay more for larger offices which may supply better services, have more modern equipment, and be more prestigious. Building age (BAGE), number of underground floors (BASE), the leasing term (TERM) and bank tenant (BANK) do not look significant at all.

Estimation results for rent and value with location and neighborhood attributes seem almost the same. In the location category, the distance from the CBD (DCBD) and the distance to the nearest station (DSTA) show statistically significant and expected

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7 The spatial functions are served online at www.spatial-econometrics.com, which is supported by the National Science Foundation BCS-0136229. To confirm the results, the SAR and the SEM were re-estimated with the GeoDA 0.9.5-i (Anselin, 2004). Command texts and estimation results will gladly be provided upon request.

Variable	OLS			SAR			SEM			SAC		
	Coeff	S.E.	t-stat	Coeff	S.E.	Asymp-t	Coeff	S.E.	Asymp-t	Coeff	S.E.	Asymp-t
Constant	906.545	85.88	10.56 **	630.690	80.77	7.81 **	904.750	87.01	10.40 **	700.701	79.20	8.85 **
Bldg. Age	2.153	2.31	0.93	-0.009	2.07	0.00	2.376	2.35	1.01	2.231	2.19	1.02
Floor Area	0.008	0.00	9.95 **	0.008	0.00	11.29 **	0.008	0.00	10.31 **	0.007	0.00	9.85 **
# of Underground	17.948	9.77	1.84	5.731	8.75	0.66	16.230	9.58	1.69	15.242	8.94	1.71
Leasing Term	-0.585	29.14	-0.02	2.822	25.85	0.11	18.830	28.47	0.66	5.231	26.61	0.20
Bank Tenant	42.905	26.07	1.65	33.003	23.09	1.43	47.139	25.79	1.83	40.323	24.12	1.67
Dist to CBD	-0.052	0.01	-9.83 **	-0.033	0.00	-6.59 **	-0.054	0.01	-10.46 **	-0.041	0.00	-8.58 **
Dist to Near Subcenter	0.004	0.00	0.77	0.004	0.00	0.87	0.006	0.00	1.22	0.005	0.00	1.27
Dist to Subway Station	-0.448	0.13	-3.40 **	-0.267	0.12	-2.26 *	-0.483	0.13	-3.78 **	-0.395	0.12	-3.31 **
LQ of Financial Inst.	35.331	9.24	3.82 **	13.110	8.35	1.57	33.013	8.95	3.69 **	22.822	8.35	2.73 **
Passenger Ridership	0.003	0.00	4.91 **	0.002	0.00	3.29 **	0.002	0.00	4.68 **	0.002	0.00	3.59 **
Zoning (Commercial)	5.781	29.39	0.20	-8.544	26.04	-0.33	16.269	29.40	0.55	11.602	27.49	0.42
DCBD×DSTA	0.057	0.01	4.97 **	0.038	0.01	3.73 **	0.063	0.01	5.72 **	0.051	0.01	4.96 **
DSUB×DSTA	-0.008	0.01	-0.81	-0.010	0.01	-1.18	-0.015	0.01	-1.58	-0.015	0.01	-1.68
Ridership×DSTA	-0.002	0.00	-2.22 *	-0.001	0.00	-1.48	-0.002	0.00	-1.88	-0.001	0.00	-1.32
ρ		NA		0.3210	0.02	13.13 **		NA		0.2010	0.01	16.23 **
λ		NA			NA		0.2529	0.01	45.01 **	0.2490	0.01	33.92 **
Adj-R^2		0.5359			0.5061			0.7253			0.7577	
σ^2		100585			78789			58314			51440	
log-likelihood		-5668			-4916			-4852			-4401	
WT Scheme		NA			DL, W2			NN, W2			NN, W1, W2	

Significance at **1% and *5%. Dependent Variable is the rent per square meter. Number of observation is 731.

DL is the abbreviation of distance limit weight scheme for spatial variables, while NN is that of k-nearest neighbor scheme.

W2=W1*W1

Table 3. Test Results of Model 1 in Rent Estimation

Variable	OLS			SAR			SEM			SAC		
	Coeff	S.E.	t-stat	Coeff	S.E.	Asymp-t	Coeff	S.E.	Asymp-t	Coeff	S.E.	Asymp-t
Constant	6187.22	501.72	12.33 **	3634.02	413.22	8.79 **	6385.17	486.68	13.12 **	3960.58	424.63	9.33 **
Dist to CBD	-0.49	0.04	-13.02 **	-0.30	0.03	-9.55 **	-0.51	0.04	-14.33 **	-0.33	0.03	-10.40 **
Dist to Near Subcenter	-0.06	0.04	-1.66	-0.03	0.03	-1.05	-0.05	0.04	-1.34	-0.02	0.03	-0.76
Dist to Subway Station	-5.85	1.05	-5.56 **	-3.76	0.82	-4.60 **	-6.25	0.99	-6.33 **	-4.16	0.82	-5.10 **
LQ of Financial Inst.	381.93	71.61	5.33 **	202.49	55.80	3.63 **	334.59	67.23	4.98 **	185.60	55.43	3.35 **
Passenger Ridership	0.04	0.00	8.90 **	0.02	0.00	6.49 **	0.04	0.00	8.99 **	0.02	0.00	6.58 **
Zoning (Commercial)	925.48	226.48	4.09 **	720.31	174.48	4.13 **	938.42	217.60	4.31 **	749.46	177.42	4.22 **
DCBD×DSTA	0.62	0.09	6.89 **	0.40	0.07	5.65 **	0.70	0.08	8.28 **	0.47	0.07	6.62 **
DSUB×DSTA	-0.03	0.08	-0.34	-0.03	0.06	-0.52	-0.08	0.07	-1.16	-0.07	0.06	-1.25
Ridership×DSTA	-0.02	0.01	-2.73 **	-0.01	0.01	-1.87	-0.02	0.01	-2.65 **	-0.01	0.01	-1.73
ρ		NA		0.40	0.02	18.81 **		NA		0.36	0.02	16.67 **
λ		NA			NA		0.26	0.00	77.41 **	0.25	0.01	27.82 **
Adj-R^2		0.5261			0.5226			0.7375			0.8226	
σ^2		6516453			3854233			3559855			2405553	
log-likelihood		-7177			-6388			-6357			-5838	
WT Scheme		NA			NN, W1			NN, W2			NN, W1, W2	

Significance at **1% and *5%. Dependent Variable is the appraised value per square meter. Number of observation is 731.
DL is the abbreviation of distance limit weight scheme for spatial variables, while NN is that of k-nearest neighbor scheme.
W2=W1*W1

Table 4. Test Results of Model 1 in Value Estimation

signs, while distance from the nearest subcenter (DSUB) is insignificant without regard to model types. In the neighborhood category, only the passenger ridership of station (PSRS) seems statistically significant throughout the models. The statistical significance of the location quotient of financial institutions (LQFI) looks clear in value estimation, while it depends on model type for rent estimation. Office tenants do not discriminate among zoning benefits of high floor coverage ratio in a commercial area (ZONE), which are concerned only about value estimation.

Primary research hypotheses are partially backed by the significance and coefficient signs of interaction variables between the DSTA and the CBD (STCB) and between the DSTA and the PSRS (STPS). Clearly, the economic benefits of station areas rely on the distance from the CBD both for rent and value, regardless of model types.

A property located one more kilometer away from the CBD loses less land value than a comparable located one less kilometer from the CBD though they are located at the same distance away from stations. Though they have equal hedonic prices or the coefficients of distance to the nearest stations (β_{DSTA}), the actual rent and value slopes of station ($\beta_{Station}$) are changed by the coefficient of interaction between the DSTA and the DCBD (β_{STCB} or $\beta_{DSTA \times DCBD}$): that is, location at one more kilometer farther from the CBD decreases the rent slope of station proximity, i.e. $\beta_{Station} = \beta_{DSTA} + \beta_{STCB} \times DCBD$, by as much as \$0.0508 and \$0.4677 per meter for rent and value estimations, respectively, in the SAC results.

For a simple example, properties A and B are located at 1 and 6 kilometers away from the CBD, respectively. Both are the same distance from the nearest stations, e.g.

100 meters. Two properties have equal value premiums for the DSTA, the negative \$416.2 ($=-4.162\times100$). However, differential in location from the CBD ($6km-1km=5km$) creates a gap between the actual value premium for each as much as \$233.9 on the grounds of the following calculation as:

$$[(-4.162+0.468\times6)\times100]-[(-4.162+0.468\times1)\times100]=-135.5-(-369.4)=233.9$$

Thus, property A loses more land value than property B with the same distance from a station. In this case, the $\beta_{Station}$ or rent slope is -\$3.694 ($=-4.162+0.468\times1$) per meter and -\$1.355 ($=-4.162+0.468\times6$) per meter, respectively. Figure 22 shows the change of $\beta_{Station}$ as the location of a property is farther away from the CBD. One thing to note, there is a critical distance preventing the $\beta_{Station}$ from being greater than zero.

The β_{DSTA} also seems to increase when an additional number of passengers use the station, a proxy for the intensity of a station's existing development or its attractiveness. Its significance seems clear in value, while it depends on model type for

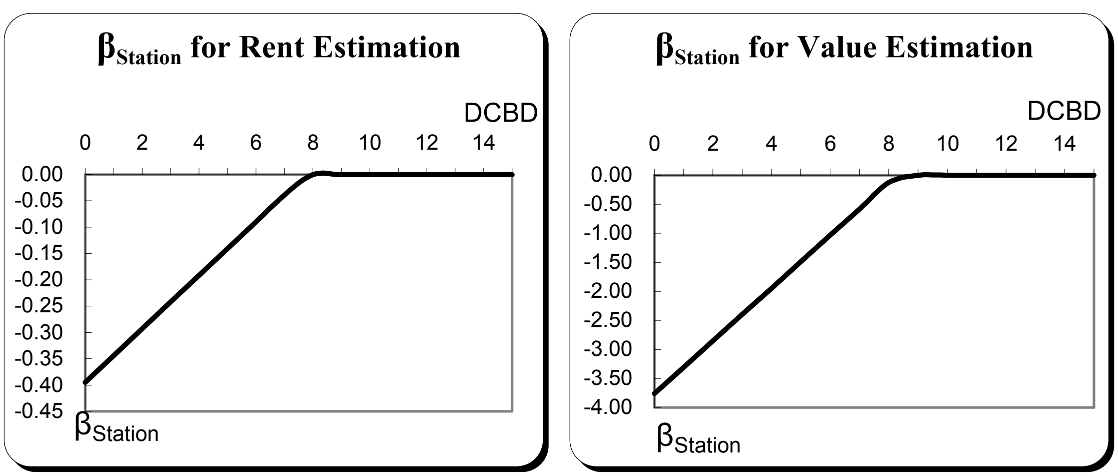

Figure 22. Change of the $\beta_{Station}$ by Distance from the CBD

rent estimation. Considering that the inclusion of spatial lag variable in the models, e.g. the SAR and the SAC, lowers the STPS's coefficients and significance, it is believed to overlap more or less with the STPS of a station area. As 1,000 passengers increase at a station, the absolute value of rent slope for station proximity ($|\beta_{Station}|$) increases as much as \$0.0012 per meter in rent and \$0.0111 per meter in value.

Table 3 shows that the MSE from the OLS in rent estimation is reduced by 21.7% with the SAR, 42.0% with the SEM and 48.9% with the SAC. The MSE from the OLS in value estimation, Table 4, is also significantly reduced up to 41.6% with the SAR, 45.1% with the SEM and 63.4% with the SAC. Tables 3 and 4 confirm that the R^2 and $Adj-R^2$ statistics from the OLS in the presence of spatial autocorrelation are obviously inflated. Another significant factor for comparing the model performance is the standard error (SE) of coefficients. Compared with the SEs of OLS estimates, those of SAR and SAC are significantly lower but those of SEM are not sure.

Estimation Results with Model 2

Tables 5 and 6 show the estimation results of Model 2 each regressed on rent and value. In the structure category, only the FLAR seems significant and shows expected positive signs regardless of model types. Regardless of estimation methods, the BAGE, the BASE, the TERM and the BANK do not seem significant nor show the expected signs. This result is the same as that from Model 1.

Location premium in the CBD is the largest, that in the SAM submarket is second highest and those in the KNM and the YDO are next. In rent estimation, the des-

Variable	OLS Coeff	OLS S.E.	OLS t-stat	SAR Coeff	SAR S.E.	SAR Asymp-t	SEM Coeff	SEM S.E.	SEM Asymp-t	SAC Coeff	SAC S.E.	SAC Asymp-t
Constant	519.9496	50.44	10.31 **	467.0400	46.18	10.11 **	512.5949	49.29	10.40 **	448.2438	49.41	9.07 **
Bldg. Age	0.5614	2.15	0.26	0.4463	1.97	0.23	0.6409	2.13	0.30	0.6786	2.06	0.33
Floor Area	0.0068	0.00	9.18 **	0.0066	0.00	9.71 **	0.0066	0.00	9.35 **	0.0062	0.00	9.04 **
# of Underground	9.2505	9.19	1.01	6.7835	8.42	0.81	8.5493	8.90	0.96	8.6442	8.61	1.00
Leasing Term	1.6806	27.00	0.06	-0.1933	24.72	-0.01	16.8377	26.15	0.64	10.3466	25.34	0.41
Bank Tenant	44.6069	24.43	1.83	30.7697	22.31	1.38	45.0398	24.05	1.87	40.7360	23.30	1.75
CBD Dummy	708.4417	62.15	11.40 **	642.9892	56.65	11.35 **	730.8046	60.03	12.17 **	616.7494	62.05	9.94 **
Kangnam Dummy	214.4359	67.88	3.16 **	187.0776	62.00	3.02 **	207.8364	68.26	3.04 **	168.1004	66.52	2.53 *
Samsung Dummy	165.4404	123.78	1.34	147.9429	113.10	1.31	173.2690	118.18	1.47	170.2087	114.44	1.49
Yoido Dummy	127.6194	88.83	1.44	95.7980	81.14	1.18	107.1216	92.32	1.16	85.5432	89.51	0.96
LQ of Financial Inst.	28.3840	9.06	3.13 **	25.4720	8.28	3.08 **	24.4081	8.69	2.81 **	19.0276	8.47	2.25 *
Passenger Ridership	0.0010	0.00	2.95 **	0.0008	0.00	2.48 *	0.0010	0.00	3.05 **	0.0008	0.00	2.58 **
Zoning (Commercial)	35.8847	26.92	1.33	27.1343	24.60	1.10	41.8655	26.78	1.56	33.9293	25.97	1.31
DSTA in CBD	-0.5748	0.20	-2.88 **	-0.5920	0.18	-3.24 **	-0.6011	0.19	-3.12 **	-0.5114	0.19	-2.73 **
DSTA in KNM	-0.3243	0.14	-2.31 *	-0.2611	0.13	-2.03 *	-0.3037	0.14	-2.14 *	-0.2367	0.14	-1.72
DSTA in SAM	-0.3302	0.25	-1.30	-0.2638	0.23	-1.14	-0.3292	0.23	-1.41	-0.3381	0.23	-1.50
DSTA in YDO	-0.2202	0.12	-1.78	-0.1673	0.11	-1.48	-0.1661	0.13	-1.29	-0.1318	0.12	-1.06
DSTA in Other Areas	-0.0220	0.03	-0.66	-0.0101	0.03	-0.33	-0.0228	0.03	-0.71	-0.0246	0.03	-0.80
ρ		NA		0.1150	0.01	15.99 **		NA		0.1290	0.02	5.31 **
λ		NA			NA		0.2540	0.01	42.88 **	0.2550	0.00	51.09 **
Adj-R^2		0.5934			0.5536			0.7624			0.7777	
σ^2		88108			73552			50221			46996	
log-likelihood		-5731			-4888			-4797			-4362	
WT Scheme		NA			NN, W2			NN, W2			NN, W1, W2	

Significance at **1% and *5%. Dependent Variable is the rent per square meter. Number of observations is 731.

DL is the abbreviation of distance limit weight scheme for spatial variables, while NN is that of k-nearest neighbor scheme.

W2=W1*W1

Table 5. Results of Model 2 in Rent Estimation

Variable	OLS			SAR			SEM			SAC		
	Coeff	S.E.	t-stat	Coeff	S.E.	Asymp-t	Coeff	S.E.	Asymp-t	Coeff	S.E.	Asymp-t
Constant	1518.51	233.68	6.50 **	882.05	190.10	4.64 **	1528.20	217.61	7.02 **	953.66	189.15	5.04 **
CBD Dummy	6476.77	459.90	14.08 **	4187.36	391.67	10.69 **	7068.90	424.19	16.66 **	4852.89	391.90	12.38 **
Kangnam Dummy	3630.37	538.02	6.75 **	2243.60	436.86	5.14 **	3816.66	521.40	7.32 **	2487.85	452.48	5.50 **
Samsung Dummy	3949.43	989.92	3.99 **	2955.45	791.40	3.73 **	4116.28	905.67	4.55 **	3584.77	771.02	4.65 **
Yoido Dummy	261.73	703.00	0.37	172.03	560.39	0.31	485.80	695.59	0.70	310.56	591.15	0.53
LQ of Financial Inst.	403.71	71.11	5.68 **	229.09	57.59	3.98 **	343.36	65.26	5.26 **	205.57	56.25	3.65 **
Passenger Ridership	0.02	0.00	5.97 **	0.01	0.00	4.61 **	0.02	0.00	6.23 **	0.01	0.00	4.87 **
Zoning (Commercial)	1303.50	205.52	6.34 **	956.42	165.08	5.79 **	1269.21	193.72	6.55 **	974.77	165.86	5.88 **
DSTA in CBD	-9.48	1.59	-5.96 **	-6.53	1.28	-5.09 **	-11.42	1.46	-7.80 **	-8.11	1.27	-6.40 **
DSTA in KNM	-3.55	1.12	-3.16 **	-2.14	0.90	-2.38 *	-3.68	1.09	-3.38 **	-2.29	0.93	-2.46 *
DSTA in SAM	-5.47	2.04	-2.68 **	-4.56	1.63	-2.81 **	-5.28	1.80	-2.94 **	-5.28	1.53	-3.46 **
DSTA in YDO	-2.44	0.99	-2.47 *	-1.54	0.79	-1.94	-2.40	0.98	-2.44 *	-1.53	0.84	-1.83
DSTA in Other Areas	-0.44	0.27	-1.64	-0.25	0.21	-1.17	-0.29	0.24	-1.18	-0.15	0.21	-0.72
ρ		NA		0.37	0.02	16.91 **		NA		0.32	0.02	14.66 **
λ		NA			NA		0.25	0.00	52.12 **	0.25	0.01	38.11 **
Adj-R^2		0.5869			0.5838			0.7789			0.8396	
σ^2		5680559			3609355			2986717			2166716	
log-likelihood		-7240			-6354			-6292			-5793	
WT Scheme		NA			NN, W1			NN, W2			NN, W1, W2	

Significance at **1% and *5%. Dependent Variable is the land value per square meter. Number of observations is 731.
DL is the abbreviation of distance limit weight scheme for spatial variables, while NN is that of k-nearest neighbor scheme.
W2=W1*W1

Table 6. Results of Model 2 in Value Estimation

cending order is slightly mixed: the coefficient of the SAM is lower than that of the KNM with the OLS, the SAR and the SEM, where this trend is reversed with the SAC. Of note is the difference between the SAM and the KNM submarkets when it is enlarged after eliminating the spatial dependency in the SAC. In neighborhood category, only PSRS seems significant throughout the models, whereas ZONE is concerned only in value estimation. The significance of the LQFI looks clear in value estimation, while it depends on model type for rent estimation.

The hierarchy of location premiums is also seen in accessibility to station, which partially backs the research hypothesis. Clearly, the coefficients of station proximity in the CBD are the greatest; with those in the SAM, the KNM and the YDO following in descending order. Though the economic benefits of transit accessibility in the overall city do not seem significant, they obviously exist in centers with high centrality and development densities.

The SAC in rent estimation, Table 5, reduces the MSE s from the OLS, the SAR and the SEM by 46.6%, 35.6% and 6.5%, respectively. In Table 6, it also lowers the MSE s in value estimation by 61.9% for the OLS, 40.0% for the SAR and 27.5% for the SEM. It is obvious that the $Adj - R^2$ statistics from the OLS are distorted and the SE s of its coefficient estimates can be reduced with the SAR and the SAC.

Spatial Autocorrelation in the OLS and SAR residuals

The parameter estimates of rho are all positive and significant, which means there are positive spatial dependencies in dependent variables. As seen in Table 7, the statistics and their marginal probabilities of Moran's I, Lagrange Multiplier (LM) and likelihood ratio (LR) test show there is a strong spatial autocorrelation in the OLS residuals. The different results are seen only in the distance inverse ($1/D$) scheme in the Wald test, both for rent and value estimations. The main reason may be that this scheme is not proper for the spatial dependency structure in dataset, which makes it perform less accurately than the others in the SAR model (Table 8).

Model	Test		Rent NN	Rent DL	Rent 1/D	Value NN	Value DL	Value 1/D
MODEL 1	Moran's I-test	Moran I	0.35	0.28	0.09	0.70	0.49	0.17
		Moran I-statistic	7.61	11.53	16.36	15.01	18.65	29.44
		Marginal Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		mean	-0.0127	-0.0102	-0.0047	-0.0113	-0.0093	-0.0044
		St. Dev.	0.0476	0.0255	0.0061	0.0476	0.0265	0.0061
	LM Tests	LM value	54.05	120.02	321.46	218.64	326.64	1050.10
		Marginal Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		chi(1) .01 value	17.61	17.61	17.61	17.61	17.61	17.61
	LR Tests	LR value	60.42	107.37	31.47	287.60	283.20	57.23
		Marginal Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		chi(1) .01 value	6.64	6.64	6.64	6.64	6.64	6.64
	Wald Tests	Wald value	349.48	1176.62	0.46	6542.42	4699.44	0.46
		Marginal Prob.	0.0000	0.0000	0.4989	0.0000	0.0000	0.4989
		chi(1) .01 value	6.64	6.64	6.64	6.64	6.64	6.64
MODEL 2	Moran's I-test	Moran I	0.27	0.18	0.04	0.77	0.54	0.08
		Moran I-statistic	5.97	7.57	7.04	1.05	14.30	33.53
		Marginal Prob.	0.0000	0.0000	0.0000	0.2306	0.0000	0.0000
		mean	-0.0167	-0.0130	-0.0054	0.7513	0.2608	0.0137
		St. Dev.	0.0476	0.0254	0.0061	0.0226	0.0196	0.0019
	LM Tests	LM value	31.67	48.07	45.52	283.82	458.93	1295.01
		Marginal Prob.	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
		chi(1) .01 value	17.61	17.61	17.61	17.61	17.61	17.61
	LR Tests	LR value	33.51	46.39	11.69	-58.17	133.58	5.45
		Marginal Prob.	0.0000	0.0000	0.0006	*NA*	0.0000	0.0196
		chi(1) .01 value	6.64	6.64	6.64	6.64	6.64	6.635
	Wald Tests	Wald value	112.83	314.93	0.46	12693.04	2868.39	0.14
		Marginal Prob.	0.0000	0.0000	0.4989	0.0000	0.0000	0.7113
		chi(1) .01 value	6.64	6.64	6.64	6.64	6.64	6.64

Table 7. Test Statistics for Spatial Autocorrelation in the OLS Residuals

WT Scheme			Rent			Price		
			NN	DL	1/D	NN	DL	1/D
M	I	LM value	96.06	370.98	239.32	2899.41	2141.01	1256.55
O		Marginal Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
D		chi(1) .01 value	6.64	6.64	6.64	6.64	6.64	6.64
E	II	LM value	818.21	1177.45	564.82	2915.33	52092.01	1320.14
L		Marginal Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
1		chi(1) .01 value	6.64	6.64	6.64	6.64	6.64	6.64
M	I	LM value	45.58	90.29	35.42	2099.84	-384.01	483.77
O		Marginal Probability	0.0000	0.0000	0.0000	0.0000	NA	0.0000
D		chi(1) .01 value	6.64	6.64	6.64	6.64	6.64	6.64
E	II	LM value	540.51	534.00	79.20	2588.23	6025	414.33
L		Marginal Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2		chi(1) .01 value	6.64	6.64	6.64	6.64	6.64	6.64

Table 8. LM Statistics for Spatial Autocorrelation in the SAR Residuals

Also, there still remains a strong spatial autocorrelation in the SAR residuals as seen in the LM test results in Table 8. The LM statistics are calculated with the same weight matrix for error term as for the spatial lag variable. Several LM statistics with the DL scheme are negative because the SAC does not outperform the SAR.

Model Performance Responding to Weight Schemes

Table 9 shows the results of the SAR. With the MSE statistics from the SAR, Model 1, the W_2 weight matrix from the DL scheme performs best in rent estimation and the W_1 matrix from the NN scheme outperforms the others in value estimation. However, it is difficult to generalize which performs best among the weight matrix schemes. With the MSE statistics from the SAR, Model 2, the W_2 weight matrix from the DL scheme performs best in rent estimation and the W_1 matrix from the NN scheme outperforms the others in value estimation. However, it is difficult to generalize which

WT Scheme			Rent			Value		
			NN	DL	1/D	NN	DL	1/D
MODEL 1	I	R^2	0.5504	0.5390	0.5876	**0.5285**	0.5077	0.5740
		Adj-R^2	0.5417	0.5300	0.5796	**0.5226**	0.5015	0.5687
		σ^2	86597	85477	86391	**3854233**	4398302	5450149
		log-likelihood	-4955	-4944	-4939	**-6388**	-6404	-6453
	II	R^2	0.4963	**0.5156**	0.5570	0.4665	0.3399	0.5431
		Adj-R^2	0.4864	**0.5061**	0.5483	0.4598	0.3316	0.5374
		σ^2	82236	**78789**	95353	4738005	4085282	6222409
		log-likelihood	-4932	**-4916**	-4974	-6425	-6375	-6502
MODEL 2	I	R^2	0.6052	0.5963	0.6272	**0.5907**	0.5787	0.6281
		Adj-R^2	0.5958	0.5866	0.6183	**0.5838**	0.5717	0.6219
		σ^2	80069	81851	79675	**3609355**	4276636	4880800
		log-likelihood	-4919	-4923	-4909	**-6354**	-6387	-6413
	II	R^2	**0.5639**	0.5851	0.6101	0.5208	0.5022	0.6025
		Adj-R^2	**0.5536**	0.5752	0.6008	0.5128	0.4939	0.5959
		σ^2	**73552**	75023	84214	4129549	3913655	5432855
		log-likelihood	**-4888**	-4894	-4929	-6374	-6356	-6452

Table 9. Summary of the SAR Results

performs best among the weight matrix schemes.

Table 10 shows the results of the SEM. To reduce the iteration times, the minimum and maximum lambdas (λ s) are set as -0.99 and 0.99, respectively. Overall, the SEM seems to outperform the SAR as seen in Table 10, reducing the MSE from SAR up to 31.7% for rent and 15.4% for value estimation. However, the result is so dependent upon the choice of weight matrix that an incorrectly chosen weight, e.g. the distance inverse scheme, makes the SEM perform poorer than the SAR. The weight matrix W_2 looks more appropriate for the error term structure in Seoul office rents than the W_1. The error terms may involve the higher-order of disturbance structure, perhaps due to second-round effects of a spatial dependency (LeSage, 1998). All the estimated

WT Scheme			Rent			Price		
			NN	DL	1/D	NN	DL	1/D
MODEL 1	I	R^2	0.5918	0.6277	0.5642	0.7213	0.7204	0.5674
		Adj-R^2	0.5839	0.6204	0.5556	0.7178	0.7169	0.562
		6^2	88330	80566	94321	3826735	3840067	5940237
		log-likelihood	-4961	-4934	-4971	-6391	-6375	-6485
	II	R^2	**0.7305**	0.6971	0.5474	**0.7408**	0.7235	0.5359
		Adj-R^2	**0.7253**	0.6911	0.5385	**0.7375**	0.7200	0.5301
		6^2	**58314**	65558	97953	**3559855**	3797281	6373127
		log-likelihood	**-4852**	-4872	-4984	**-6357**	-6357	-6510
MODEL 2	I	R^2	0.6255	0.6374	0.6094	0.7346	0.7163	0.6136
		Adj-R^2	0.6166	0.6288	0.6001	0.7301	0.7115	0.6072
		6^2	81038	78461	84531	3644678	3896317	5305325
		log-likelihood	-4922	-4914	-4931	-6360	-6368	-6444
	II	R^2	**0.7679**	0.7067	0.6038	**0.7825**	0.7302	0.5956
		Adj-R^2	**0.7624**	0.6997	0.5943	**0.7789**	0.7257	0.5889
		6^2	**50221**	63470	85753	**2986717**	3705351	5552983
		log-likelihood	**-4797**	-4856	-4936	**-6292**	-6343	-6460

Table 10. Summary of the SEM Results

lambda(λ)s are significant and positive, implying that there are unknown omitted key variables in the OLS regression models.

In the SAC results, Table 11, there does not seem to be any regularity in regard to which combination of W_1 and W_2 performs the best among the possible combinations. Though, the combination of W_1 for spatial lag and W_2 for error term, both from the NN scheme, outperforms the others, implying that weighting the nearby properties is more compatible with the research data. Similar to the SEM model, the SAC is so vulnerable to the choice of weight matrix that it underperforms the SAR or the SEM with improper weight matrices. Generally, it significantly reduces the MSE s of the SAR and the SEM, and all the rho and lambda estimates are significant and positive.

WT Scheme			Rent			Value		
			NN	DL	1/D	NN	DL	1/D
MODEL 1	W1 W2	R^2	**0.7623**	0.7021	0.6720	**0.8248**	0.7462	0.7416
		Adj-R^2	**0.7577**	0.6963	0.6656	**0.8226**	0.7430	0.7384
		σ^2	**51440**	64474	70975	**2405553**	3485614	3548321
		log-likelihood	**-4401**	-4445	-4448	**-5838**	-5911	-5878
	W2 W1	R^2	0.6498	0.6609	0.6625	0.7532	0.7393	0.7577
		Adj-R^2	0.6430	0.6543	0.6559	0.7502	0.7360	0.7547
		σ^2	75786	73386	73036	3388416	3579993	3327024
		log-likelihood	-4493	-4479	-4459	-5926	-5919	-5855
MODEL 2	W1 W2	R^2	**0.7828**	0.7097	0.6756	**0.8422**	0.7504	0.7448
		Adj-R^2	**0.7777**	0.7028	0.6679	**0.8396**	0.7462	0.7405
		σ^2	**46996**	62823	70198	**2166716**	3427851	3504265
		log-likelihood	**-4362**	-4434	-4444	**-5793**	-5902	-5874
	W2 W1	R^2	0.6782	0.6654	0.6612	0.7706	0.7375	0.7616
		Adj-R^2	0.6705	0.6574	0.6532	0.7668	0.7331	0.7576
		σ^2	69644	72415	73311	3150017	3604778	3273714
		log-likelihood	-4456	-4466	-4460	-5887	-5913	-5849

Table 11. Summary of the SAC Results

Chapter Summary

This study designs two estimation models to test the research questions: Model 1 measures influence on station benefits by distance from centers, e.g. the CBD and subcenters, and by development density. Model 2 examines the existence of submarkets regarding station proximity. Clearly, the $\beta_{Station}$ relies on distance from the CBD both for rent and value, regardless of model types. It is also affected by the PSRS of each station, specifically in value estimation. As a result, the $\beta_{Station}$ is discriminated by location in the city: the $\beta_{Station}$ in the CBD is the highest while those in submarkets are next. The capitalization of station proximity in other areas is so small that its coefficient looks insignificant.

BAGE, BASE, TERM and BANK do not look significant at all, regardless of model types. The constant significances of FLAR imply that there exists the size effect in office submarkets, which is exactly congruent with the conclusions of literature on office rents (Bollinger et al., 1998; Dunse et al., 1998 and 2001; Glascock et al., 1990).

In Model 1, distance from the CBD (DCBD) and the nearest subway station (DSTA) are always significant while distance from the nearest subcenter (DSUB) is insignificant without regard to model types. Also, a couple of location dummies, i.e. CBD and KNM in Model 2 always show statistical significances. Overall, PSRS seems significant throughout the estimation models, while the statistical significance of LQFI looks clear in value estimation but depends on model type for rent estimation. Also, ZONE is influential only in value estimation.

On the grounds of the statistics of R^2, $Adj-R^2$, MSE and log-likelihood as well as the SE s and absolute values of coefficients, the estimation with spatial models, i.e. the SAR, the SEM and the SAC, outperforms the OLS estimation which is distorted in the presence of spatial autocorrelation. Also, there may be a strong spatial autocorrelation even in the SAR residuals when the effect of omitting important variables still remains. Clearly, under the spatial autocorrelation, biased are the R^2 s and $Adj-R^2$ s not only from the OLS but also from the SAR. Thus, the spatial error term variable seems more useful than the lag variable in this study. Also, selecting an appropriate scheme critically decides the performances of estimation models containing error terms. There may exist a unique weight scheme proper for the autocorrelation structure in residuals. In this study, one nearest neighbor scheme seems appropriate for the error term structure in Seoul office rents.

CHAPTER VII

DISCUSSION AND CONCLUSIONS

Findings and Contributions of the Study

This study suggests a potential systematic bias in measuring land value premiums for station proximity by location in the city and a refined model specification to correlate the premiums with distance to centers and development density. This is expected to reduce bias more efficiently. Applying the bid rent model in which all the travel costs are more rapidly capitalized by a shorter distance to the CBD due to substitution to transit impact on land values, it develops a theoretical foundation and provides empirical evidence for transit's discriminant impact by location and density.

Examining 731 office rentals and land values in Seoul, this study found that commercial rents and land values show similar responses to location attributes, specifically to station proximity. Office rents and land values in Seoul show that the actual stations' economic benefit ($\beta_{Station}$) decays with increasing distance from the CBD and significantly depends on the development densities of station areas. With distance to stations being equal, one more kilometer from the CBD reduces the $\beta_{Station}$ as much as \$0.0508 and \$0.4677 per meter for rent and value estimations, respectively. The $\beta_{Station}$ also seems to increase with an increased number of passengers using the station, a proxy for the development densities of station areas. With a 1,000 passenger increase at a station, the absolute value of $\beta_{Station}$ increases as much as \$0.0012 per meter in rent and \$0.0111 per meter in value. As a result, the economic benefits of accessibility to transit stations are discriminated even in a single real estate market: the $\beta_{Station}$ in the CBD is the highest while those in subcenters are next. The $\beta_{Station}$ in other areas is so small that its coefficient does not seem significant or consequential.

However, these findings are not applicable to the exogenous transit impact on land use change which is more beneficial in non-urban suburbs than in the CBD. The study findings regarding the endogenous transit impact on land values in a well developed urban area explain why an additional transit investment would not be an incentive for a residential suburb to change its land use into higher density use, specifically when it has some accessibility to the CBD.

Overall, rent and value premiums over station proximity seem to exist in the Seoul office market, but they are obviously seen in centers with higher centrality and development densities. In a city like Seoul, a spatially constrained city where expansion is very limited, a new transit investment may reinforce the centrality of centers and facilitate the concentration of business entities.

The SE s and absolute values of coefficient estimates as well as the statistics of R^2, $Adj-R^2$, MSE and log-likelihood ratios suggest that the estimation with spatial models outperforms the OLS estimation in the presence of spatial autocorrelation. Of note is that the R^2 and $Adj-R^2$ statistics from the OLS are biased. Also, there may be a strong spatial autocorrelation even in the SAR residuals. Overall, spatial lag and error term variables greatly improve the fitness of regression equations; however, the latter seemed more useful than the former in this study.

Policy Implications

A poor specified model in the hedonic approach does not capture the exact transit impact on land values. A study heavily sampled from centers may find a significantly large premium over station proximity, whereas one concentrated in the suburbs may not find the same station benefit as in the inner city. The inconsequential impact of transit station on land value may be found in the city where the economic benefit actually exists. Also, due to the incongruence of station area with station value-added area, using a dummy variable based on walking distance from a station seems intrinsically risky. Since the interval between stations decreases by a shorter distance to the CBD, a poorly defined dummy may measure the economic benefits of other stations. More important, this tendency does not solely belong to a transit system but to all transportation modes with traffic nodes, e.g. highway ramps.

In this study, the discriminant land value premiums by location in the city cast doubt on practices using a 500-meter radius scheme to delineate the planning boundaries for various station areas. A densely developed area close to the CBD is more narrowly influenced by a transit station than a comparable area in the suburbs. Thus, it is unnecessary to apply a common distance limit to all station areas in the city.

The potential for more compact and denser developments within station areas seems higher in dense inner cities, providing compelling evidence for the concept of 'compact city' which advocates higher density development in the inner city depending on public transportation. Also, the research results are applicable to the concept of 'value capture,' one of the most important rationales for transit joint development. This concept proposes that a transit development with expropriated properties near stations can finance project costs by increased land values and real estate taxes. The potential for this financing looks promising only in the suburbs which are not yet developed or have limited accessibility to business centers.

In another research interest, spatial autocorrelation, there is a weak tendency of declining absolute values of coefficients only for the variables which are statistically significant, but there is a fine line to be generalized because of counter results. However, it is clear that it is risky to obtain exaggerated model performances and inflated parameter estimates in the presence of spatial autocorrelation. Considering the significantly lower SE s of coefficients from the spatial models, more robust and stable estimates can be achieved in a spatially dependent real estate market.

Limitations of Study and Suggestions for Future Research

This study has three major limitations in its methodology which need to be refined by future research: the validity of a proxy variable, the unique characteristic of the study area and unrealistic assumptions about spatially autocorrelated error structure. Based on the trip generation model, it used passenger ridership as a proxy for the development density of a station area. Also, passenger ridership is used as a proxy because of unavailability of GIS data regarding this information. However, it is probable in most cases that passenger ridership not solely reflects the physical development density or land use intensity of a station area but also various economic and transportation factors, e.g. employment size and the passengers' modal choices or modal propensities. This is the most critical weakness of the study regarding development density. A desirable alternative approach to the proxy used in the study could be an index from the physical development density or land use intensity of a station area within a certain radius limit from each property.

Of note is the ratio of Seoul's development density and transit share to total transportation trips. Since transit impact on land value is more easily capitalized in a dense city and passenger ridership is significantly related to the economic benefits of station area, a city with lower density or with a poor transit share may generate different results.

This study suggests another possible conceptual distance approach for future research, that is, a travel time concept instead of the shortest walking distance to a transit station. Since the bid rent model implicitly assumes a travel time distance equal for any location with the same access time to the CBD, the former approach may have a stronger theoretical foundation. In reality, however, it is more probable that it is a physical distance concept. That is why this study used the latter scheme. In a study area where auto transportation is prevalent, a travel time measure may show meaningful coefficients.

Finally, this study relies upon a weight scheme which implicitly assumes the spatial autocorrelation structure in advance. There may exist a unique weight scheme proper for the data structure which cannot be known in advance. Since selecting an appropriate scheme critically decides the error model performance, detecting the spatial autocorrelation structure will be an issue for further study of spatial models in urban areas.

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APPENDIX

Correlation Relationship between Research Variables

	RENT	VALUE	BAGE	FLAR	LAND	STO	BASE	FCR	EFFR	PARK	ELEV	HAC	TERM	FINC	BANK
RENT															
VALUE	*0.71*														
BAGE	0.21	0.30													
FLAR	*0.58*	0.47	0.06												
LAND	0.32	0.23	0.05	*0.63*											
STO	*0.56*	*0.52*	0.03	*0.79*	0.42										
BASE	0.42	0.40	-0.24	*0.54*	0.24	*0.67*									
FCR	0.48	*0.53*	-0.04	*0.52*	0.05	*0.79*	*0.73*								
EFFR	-0.20	-0.20	0.16	-0.25	-0.20	-0.37	*-0.58*	-0.38							
PARK	0.08	0.12	0.18	0.07	0.01	0.07	-0.02	0.11	0.09						
ELEV	*0.57*	0.45	0.09	$\boxed{0.92}$	*0.57*	$\boxed{0.80}$	*0.50*	*0.52*	-0.25	0.08					
HAC	0.29	0.31	0.06	0.29	0.19	0.41	0.45	0.42	-0.39	0.01	0.30				
TERM	-0.35	-0.30	-0.29	-0.31	-0.21	-0.33	-0.20	-0.27	0.09	-0.08	-0.31	-0.15			
FINC	0.26	0.31	0.15	0.26	0.12	0.25	0.24	0.25	-0.20	-0.01	0.25	0.27	-0.07		
BANK	0.27	0.31	0.16	0.29	0.15	0.25	0.21	0.22	-0.12	0.00	0.28	0.22	-0.12	*0.63*	
LQFI	0.41	0.43	0.20	0.30	0.18	0.37	0.33	0.37	-0.28	0.05	0.32	0.28	-0.31	0.13	0.11
PSRS	0.33	0.48	0.10	0.19	0.14	0.25	0.26	0.29	-0.18	0.00	0.17	0.22	-0.07	0.14	0.10
COMM	0.37	0.44	0.21	0.32	0.11	0.46	0.36	0.48	-0.20	0.05	0.33	0.32	-0.33	0.29	0.19
SEMR	-0.15	-0.18	-0.11	-0.12	-0.09	-0.13	-0.11	-0.10	0.14	-0.03	-0.13	-0.09	0.09	-0.12	-0.08
SEMI	-0.08	-0.11	-0.04	-0.03	0.03	-0.06	-0.01	-0.10	-0.07	-0.02	-0.05	-0.04	0.03	0.00	-0.03
NONR	0.28	0.32	0.13	0.25	0.09	0.39	0.31	0.42	-0.14	0.04	0.25	0.27	-0.29	0.23	0.14
DCBD	*-0.55*	*-0.52*	-0.37	-0.38	-0.18	-0.40	-0.28	-0.35	0.08	-0.09	-0.39	-0.32	*0.52*	-0.20	-0.26
DSUB	-0.10	-0.15	-0.11	-0.12	-0.13	-0.19	-0.24	-0.14	0.34	0.01	-0.13	-0.21	0.04	-0.05	-0.10
DSTA	-0.22	-0.29	-0.11	-0.12	0.00	-0.13	-0.12	-0.15	-0.01	-0.03	-0.11	-0.11	0.13	-0.18	-0.08
CBD	*0.67*	*0.59*	0.30	0.43	0.21	0.44	0.31	0.41	-0.07	0.10	0.42	0.23	-0.45	0.17	0.22
KNM	0.02	0.18	0.03	-0.04	0.06	-0.01	0.11	0.01	-0.17	-0.03	-0.02	0.17	0.16	0.04	0.08
SAM	0.01	0.11	-0.04	0.01	0.00	0.03	0.12	0.09	-0.14	-0.02	0.00	0.10	0.04	-0.04	0.01
YDO	0.00	-0.08	0.11	0.11	0.07	0.13	0.08	0.07	-0.20	0.02	0.14	0.10	-0.18	0.04	-0.02

Table 12. Bi-Variate Pearson's Correlation Coefficients between Research Variables

	LQFI	PSRS	COMM	SEMR	SEMI	NONR	DCBD	DSUB	DSTA	CBD	KNM	SAM	YDO
RENT													
VALUE													
BAGE													
FLAR													
LAND													
STO													
BASE													
FCR													
EFFR													
PARK													
ELEV													
HAC													
TERM													
FINC													
BANK													
LQFI													
PSRS	0.33												
COMM	0.30	0.30											
SEMR	-0.03	-0.21	-0.43										
SEMI	-0.08	-0.12	-0.18	-0.06									
NONR	0.28	0.14	*0.72*	0.23	0.10								
DCBD	-0.32	-0.18	-0.40	0.12	0.12	-0.31							
DSUB	-0.20	-0.22	-0.10	0.11	-0.04	-0.04	0.08						
DSTA	-0.13	-0.13	-0.20	0.01	0.07	-0.17	0.24	-0.10					
CBD	0.36	0.23	0.33	-0.13	-0.07	0.25	*-0.73*	0.11	-0.22				
KNM	-0.03	0.30	0.01	-0.12	-0.05	-0.09	0.03	-0.38	-0.02	-0.14			
SAM	0.11	0.25	0.02	-0.08	-0.03	-0.05	0.09	-0.28	0.01	-0.10	-0.07		
YDO	0.25	-0.04	0.18	-0.08	-0.04	0.13	-0.03	-0.33	0.14	-0.12	-0.08	-0.06	

Table 12. (*Continued*)

RENT: Office rent per leased area ($\$/m^2$)
Value: Appraised land value per unit ($\$/m^2$)
BAGE: Building age
FLAR: Total floor area of an office property
LAND: Land area of an office property
STO: Number of floors above the ground
BASE: Number of underground floors
FCR: Floor coverage ratio
EFFR: Efficiency ratio of leased space
PARK: Floor area per one parking permit
ELEV: Number of elevators
HAC: Individual heating and air conditioning controllability, one if centrally controlled
TERM: Leasing term, one for Chonse contract and zero for monthly rent
FINC: Dummy variable with one if there is any financial institution in the building
BANK: Dummy variable with one if there is any bank in the building
LQFI: Location quotient of financial institutions in the local administrative district
PSRS: Passenger ridership of a station
COMM: Dummy variable with one if a property belongs to a commercial area
SEMR: Dummy variable with one if a property belongs to a semi-residential area
SEMI: Dummy variable with one if a property belongs to a semi-industrial area
NONR: Dummy variable with one if a property belongs to a non-residential area
DCBD: Distance from the CBD
DSUB: Distance from the nearest subcenter
DSTA: Distance from the nearest transit station
CBD: Location dummy denoting if a property belongs to the CBD submarket
KNM: Location dummy denoting if a property belongs to the Kangnam submarket
SAM: Location dummy denoting if a property belongs to the Samsung submarket
YDO: Location dummy denoting if a property belongs to the Yoido submarket

Table 12 shows the bivariate correlation coefficients between all the research variables and their related variables in the SAMS dataset. ELEV causes strong collinearity with FLAR and STO. STO is also modestly linearly related to BASE, FLAR and FCR, and FCR to BASE. Also, BANK and FINC look correlated with each other. There seem collinearity between COMM and NONR and between DCBD and CBD. It is desirable not to insert them in a model, which may cause a multi-collinearity problem.

Model Development: Independent Variables in Structure Category

Table 13 is the estimation result from regressing the rent on all the independent variables in the structure category. There is a strong multi-collinearity between FLAR, STO, FCR and ELEV. A single variable, FLAR, seems enough for these four variables because it looks significant in the estimation and has been regarded a challenging resear-

R	R^2	Adj-R^2	SE of the Estimate
0.6625	0.4389	0.4287	351.95

	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	328.676	139.345	2.36	0.0186		
BAGE	11.548	2.387	4.84	0.0000	0.7255	1.3785
FLAR	0.005	0.002	2.78	0.0057	0.1190	8.4062
LAND	0.006	0.006	0.95	0.3432	0.4426	2.2595
STO	-5.592	5.684	-0.98	0.3256	0.1454	6.8772
BASE	26.121	14.271	1.83	0.0676	0.2803	3.5679
FCR	29.163	8.695	3.35	0.0008	0.1966	5.0862
EFFR	131.123	166.030	0.79	0.4299	0.6054	1.6518
PARK	-0.054	0.184	-0.29	0.7713	0.9333	1.0714
ELEV	23.003	10.392	2.21	0.0272	0.1333	7.4999
HAC	29.559	37.646	0.79	0.4326	0.7060	1.4165
TERM	-110.466	29.720	-3.72	0.0002	0.7883	1.2685
FINC	40.426	35.443	1.14	0.2544	0.5628	1.7769
BANK	35.506	35.436	1.00	0.3167	0.5763	1.7351

Table 13. OLS Estimation with all the Structural Variables

R	R^2	Adj-R^2	SE of the Estimate
0.6475	0.4193	0.4153	355.96

	Unstandadized Beta	**S.E.**	**t**	**Significance**	**Tolerance**	**VIF**
(Constant)	482.776	53.244	9.07	0.0000		
BAGE	13.513	2.332	5.79	0.0000	0.7774	1.2864
FLAR	0.009	0.001	11.07	0.0000	0.6261	1.5973
BASE	56.165	9.795	5.73	0.0000	0.6077	1.6456
TERM	-119.889	29.636	-4.05	0.0001	0.8095	1.2354
BANK	66.598	28.975	2.30	0.0218	0.8810	1.1350

Table 14. OLS Estimation with the Selected Structure Variables

ch variable in literature. LAND, EFFR, PARK and HAC does not seem significant at all. Also, this study chooses only BANK among FINC and BANK which are highly correlated with each other because it has the higher correlation coefficient with RENT.

Table 14 is the result of reduced model with five structural independent variables, i.e. BAGE, FLAR, BASE and TERM. Though its $Adj-R^2$ is slightly lowered and the SE of its estimation is increased a little, it is more desirable than that in Table 13 on the grounds of the rule, 'parsimoniousness,' and irrelevance to the collinearity problems.

Model Development: Independent Variables in Neighborhood Category

Table 15 shows the regression results on rent and value. Estimation results for rent and value with neighborhood attributes look almost the same. Variables related to the zoning ordinance, i.e. COMM, SEMR, SEMI and NONR are multi-collinearly related with one another, which inflates the variance inflation factors (VIF s) of their parameter estimates. Since COMM has the highest bi-variate Pearson's correlation coefficients with RENT and VALUE, this study selects it only among the zoning variables. Table 16 shows the results of reduced models with LQFI, PSRS and COMM. The $Adj - R^2$ statistics and the SE of estimates are almost the same as those of the previous models.

Dependent	R	R^2	Adj-R^2	SE of the Estimate
Rent	0.5083	0.2584	0.2522	402.55

RENT	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	490.019	35.782	13.69	0.0000		
LQFI	87.017	10.905	7.98	0.0000	0.8290	1.2063
PSRS	0.002	0.000	4.67	0.0000	0.8265	1.2099
COMM	-292.930	403.619	-0.73	0.4682	0.0055	180.2166
SEMR	-523.050	405.916	-1.29	0.1980	0.0127	78.7072
SEMI	-488.877	414.605	-1.18	0.2387	0.0537	18.6243
NONR	519.149	404.074	1.28	0.1993	0.0067	149.9456

Dependent	R	R^2	Adj-R^2	SE of the Estimate
Value	0.6159	0.3794	0.3742	2933.40

VALUE	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	688.090	260.749	2.64	0.0085		
LQFI	621.439	79.463	7.82	0.0000	0.8290	1.2063
PSRS	0.029	0.003	9.71	0.0000	0.8265	1.2099
COMM	-3105.714	2941.202	-1.06	0.2914	0.0055	180.2166
SEMR	-5042.279	2957.942	-1.70	0.0887	0.0127	78.7072
SEMI	-5263.443	3021.258	-1.74	0.0819	0.0537	18.6243
NONR	5149.731	2944.515	1.75	0.0807	0.0067	149.9456

Table 15. OLS Estimation with all the Neighborhood Variables

Dependent	R	R^2	Adj-R^2	SE of the Estimate
Rent	0.5066	0.2566	0.2535	402.20

RENT	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	491.700	31.056	15.83	0.0000		
LQFI	86.482	10.775	8.03	0.0000	0.8476	1.1798
PSRS	0.002	0.000	4.80	0.0000	0.8488	1.1781
COMM	223.785	32.349	6.92	0.0000	0.8623	1.1596

Dependent	R	R^2	Adj-R^2	SE of the Estimate
Value	0.6137	0.3767	0.3741	2933.73

VALUE	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	717.573	226.527	3.17	0.0016		
LQFI	621.282	78.594	7.90	0.0000	0.8476	1.1798
PSRS	0.029	0.003	9.91	0.0000	0.8488	1.1781
COMM	1999.103	235.960	8.47	0.0000	0.8623	1.1596

Table 16. OLS Estimation with the Selected Neighborhood Variables

Model Development: Estimation with All Categories

Table 17 shows the estimation results of Model 1 each regressed on rent and value, which are almost the same as Tables 3 and 4 in the body. In the structure category, only total floor area of building (FLAR) and the number of subterranean floors (BASE) seem significant and show expected positive signs. Building age (BAGE), leasing term (TERM) and the existence of bank tenant (BANK) do not seem statistically significant. In the location category, the distance from the CBD (DCBD) and the distance to the nea rest station (DSTA) show statistically significant and expected signs, while distance from the nearest subcenter (DSUB) is insignificant. In the neighborhood category, the passenger ridership of station (PSRS) and the location quotient of financial institutions (LQFI) seem statistically significant. The zoning benefit of high floor coverage ratio in a

Dependent	R	R^2	Adj-R^2	SE of the Estimate
Rent	0.7229	0.5225	0.5152	324.13

RENT	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	739.726	75.997	9.73	0.0000		
BAGE	3.542	2.352	1.51	0.1325	0.6340	1.5774
FLAR	0.008	0.001	10.26	0.0000	0.6108	1.6371
BASE	21.625	9.956	2.17	0.0302	0.4877	2.0505
TERM	-6.595	29.746	-0.22	0.8246	0.6662	1.5011
BANK	41.846	26.614	1.57	0.1163	0.8659	1.1549
DCBD	-0.033	0.004	-8.43	0.0000	0.5595	1.7874
DSUB	0.005	0.003	1.61	0.1080	0.8549	1.1697
DSTA	-0.068	0.034	-2.02	0.0442	0.8982	1.1133
LQFI	36.815	9.355	3.94	0.0001	0.7303	1.3694
PSRS	0.002	0.000	4.93	0.0000	0.8043	1.2433
COMM	12.771	28.990	0.44	0.6597	0.6974	1.4340

Dependent	R	R^2	Adj-R^2	SE of the Estimate
Value	0.6976	0.4867	0.4824	2667.69

VALUE	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	4607.520	421.521	10.93	0.0000		
DCBD	-0.296	0.027	-10.82	0.0000	0.7753	1.2899
DSUB	-0.026	0.027	-0.96	0.3387	0.9119	1.0966
DSTA	-1.175	0.275	-4.27	0.0000	0.9024	1.1081
LQFI	415.402	73.987	5.61	0.0000	0.7909	1.2644
PSRS	0.028	0.003	10.26	0.0000	0.8209	1.2182
COMM	1044.464	227.881	4.58	0.0000	0.7645	1.3081

Table 17. OLS Estimation with Model 1

Dependent	R	R^2	Adj-R^2	SE of the Estimate
Rent	0.7713	0.5948	0.5875	298.99

RENT	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	539.578	50.393	10.71	0.0000		
BAGE	0.788	2.158	0.37	0.7151	0.6408	1.5606
FLAR	0.007	0.001	9.47	0.0000	0.5882	1.7000
BASE	8.339	9.231	0.90	0.3667	0.4827	2.0718
TERM	0.331	27.096	0.01	0.9903	0.6832	1.4638
BANK	43.197	24.532	1.76	0.0787	0.8672	1.1532
CBD	577.152	42.078	13.72	0.0000	0.5068	1.9732
KNM	102.032	43.896	2.32	0.0204	0.7623	1.3118
SAM	37.621	58.165	0.65	0.5180	0.8386	1.1925
YDO	14.560	51.975	0.28	0.7795	0.7525	1.3290
DSTA	-0.065	0.031	-2.10	0.0360	0.8995	1.1117
LQFI	27.081	8.992	3.01	0.0027	0.6726	1.4867
PSRS	0.001	0.000	2.88	0.0041	0.6669	1.4995
COMM	37.755	26.944	1.40	0.1616	0.6869	1.4558

Dependent	R	R^2	Adj-R^2	SE of the Estimate
Value	0.7536	0.5679	0.5632	2450.90

VALUE	Unstandadized Beta	S.E.	t	Significance	Tolerance	VIF
(Constant)	1752.121	233.756	7.50	0.0000		
CBD	4418.034	296.505	14.90	0.0000	0.6858	1.4581
KNM	2452.559	346.933	7.07	0.0000	0.8200	1.2195
SAM	1829.697	471.288	3.88	0.0001	0.8583	1.1651
YDO	-847.532	412.665	-2.05	0.0404	0.8021	1.2468
DSTA	-0.979	0.253	-3.88	0.0001	0.9042	1.1059
LQFI	398.650	72.104	5.53	0.0000	0.7029	1.4227
PSRS	0.016	0.003	5.81	0.0000	0.6729	1.4861
COMM	1333.169	209.706	6.36	0.0000	0.7620	1.3124

Table 18. OLS Estimation with Model 2

commercial area (COMM) is concerned only about value estimation. Table 18 shows the estimation results of Model 2 each regressed on rent and value. Only FLAR seems significant and shows expected signs in the structure category. BAGE, BASE, TERM and BANK do not seem significant at all. All the location variables seem significant in value estimation, while SAM and YDO look inconsequential in rent estimation. In the neighborhood category, PSRS and LQFI seem statistically significant. COMM looks consequential only in value estimation. Above results are mostly congruent with the interpretations of Tables 5 and 6 in the body.

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